Risk and Reliability Assessment of Marine Operations

By

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Abstract

Marine structures are widely used in the oil and gas industry, marine transportation and exploration areas and renewable energy applications. Understanding dynamic behaviour of these structures is necessary to allow their evaluation under the effects of environmental loads such as wave, wind and currents. However, the sea environment is very complex, and the response of these structures is affected by considerable uncertainties that should be predicted accurately. Due to the stochastic trend of the sea environment, different types of failure are expected to be observed during the life time of a structure. Consequently, failure of a marine structure may pose various major risks in terms of environmental pollution and loss of assets for companies. Therefore, a great deal of research on the improvement of marine safety is carried out to mitigate the associated risks. It is also necessary to take into account the process of risk escalation in a more realistic way than relying only on either precursor data or expert judgments. This requires a comprehensive approach when it comes to accident modelling and risk analysis of marine structures. This PhD research is focused on developing advanced probabilistic models for representing dynamic risk assessment of marine structures in a harsh environment. The developed frameworks will assist industries to model marine accidents and improve the reliability of marine structures to minimize the risk of failure. The main content of the thesis investigates a developing practical framework for incorporating the reliability of floating offshore structures while considering hydrodynamic performance of the structure as real monitoring data based on modelling the physics of the failure. In order to evaluate response of the marine structure in harsh environment, the storm condition was developed to help researchers to generate necessary data for conducting reliability assessment of the system. The outcome of this achievement led to analysis performance of either the marine structure or the human on board for future risk analysis and decision-making. As a result, the developed methodologies include time-dependent reliability strategies that can model long-term failure scenarios in marine environment which is able to consider marine accident and human failure in respect to the time of operations. Overall, this thesis provides a comprehensive probability model for evaluating the dynamic risk assessment of marine structures under different operational conditions. The outcome of this research will assist industries to improve the reliability of the structures in the design phase or in their operating conditions to mitigate the associated risks to assets, human life and the environment.

Keywords: Reliability engineering, Safety analysis, Risk assessment, Marine system, Hydrodynamic, Human factors, Bayesian Network

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Declaration and Statements

Declaration of Originality

I declare that this is my own work and has not been submitted in any form for another degree or diploma at any university or other institution of tertiary education. Information derived from the published or unpublished work of others has been duly acknowledged in the text and a list of references if given.

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No research ethics approval was needed during my PhD study at the University of Tasmania.

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Dedication

Dedicated to my beloved Grandfather **Amin-Allah Rafiei** and my best friend's Mother **Afsane ShahrAshob** whom both passed away before submitting this thesis

"*Life is not the opposite of the death.*

Death is the opposite of the birth. Life is Eternity".

Eckhart Tolle

Thesis by Journal Articles

The following four published/accepted and one under review journal articles constitute the content of this thesis.

- Chapter 2 **M.M. Abaei**, R. Abbassi, V. Garaniya, S. Chai, Reliability Assessment of Marine Floating Structures Using Bayesian Network, Journal of Applied Ocean Research, Vol. 76, 2018, Pages 51-60

- Chapter 3: **M.M. Abaei**, E. Arzaghi, R. Abbassi, V. Garaniya, F. Khan. A Robust Risk Assessment Methodology For Safety Analysis of the Marine Structures Under Storm Conditions, Journal of Ocean Engineering, 2018, Vol. 156, Pages 167–178

- Chapter 4: **M.M. Abaei**, E. Arzaghi, R. Abbassi, V. Garaniya, S. Chai, A Novel Approach for safety Analysis of Floating Structure Encountering Storm Conditions, Journal of Ocean Engineering, Vol. 150, 2018, Pages 397-403.

- Chapter 5: **M.M. Abaei**, E. Arzaghi, R. Abbassi, V. Garaniya, M.R. Javanmardi, S. Chai, Reliability Assessment of Ship Grounding Using Bayesian Inference, Journal of Ocean Engineering, Vol. 159, 2018, Pages 47-55

- Chapter 6: **M.M. Abaei**, R. Abbassi, V. Garaniya, E. Arzaghi, A. Bahoo Toroody, S. Chai. Dynamic Human Reliability Model Developed for Marine and Offshore Operations in Harsh Environment.

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List of Symbols and Abbreviations

α	shape parameter
α_k	crest elevation
β	scale parameter/ coefficient that refers to maximum wave height in each sea spectrum
B	breadth of ship (m)
d_i	decision alternative
$\vec{e}_i$	direction of the force excreted in *i*th direction
$EU\left(d_i\right)$	expected utility
η_{ICNW}	surface elevation of ICNW
$\eta_{R_k}(t)$	k^{th} step sea wave profile
f	probability density function
φ	generic distribution function
$FD(\theta_n)$	Flooded Decision in nth Degree
$FU(\theta_n)$	Flooded Utility in nth Degree
H	water depth (m)
H_s	significant wave height
H_{Max_k}	most probable maximum wave height in the sea state k
$IU(\theta_n)$	Intact Utility in nth Degree
$ID(\theta_n)$	Intact Decision in nth Degree
L	overall length of ship (m)
λ	failure rate
m	mass (kg)
m_{2k}	second spectral moment
$\vec{n}$	normal vector
N_W	number of wave cycles during the storm period (t_d)
P	Pressure
$pa\left(X_i\right)$	the parent set of variable X_i
$p(H_s)$	Long-term probability distribution of significant wave height
$p(H_{storm})$	Probability of different level of storm condition encountered by ICNW profile
$p\left(FR(\theta_n)\right)$	Flooded Response in n^{th} degree
$p\left(IR(\theta_n)\right)$	Intact Response in n^{th} Degree

$\vec{r}$	position vector (m)
ρ	water density
$\rho_k(t)$	unit new wave autocorrelation function
$\dot{\rho}_k(t)$	slope new wave autocorrelation function
$S(\omega)$	sea spectrum
T	static draft (m)
T_p	peak spectral period
t_d	constant storm period time
t	time (sec)
t_i	time of *i*th observation / travelling time of the vessel
θ_m	maximum angle of positive stability
θ_s	static angle of inclination after damage
θ	roll angle
V_∞	far-field particle's velocity
V_s	ship speed (m/s)
Z	dynamic squad
σ_k	variance of the wave energy spectrum
BN	Bayesian network
CPT	conditional probability table
DBN	Dynamic Bayesian network
DUKC	dynamic under keel clearance
EWA	endurance wave analysis
FSU	floating storage unit
GEV	generalized extreme value
HBA	hierarchical Bayesian approach
ICNW	intensifying constrained new wave model
MLE	maximum likelihood estimation
NHPP	nonhomogeneous Poisson process
PDF	probability density function
SCZ	safe clearance zone
SL	safe limit
SWL	still water level
UCZ	unsafe clearance zone
UKC	

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1. Introduction

1.1 Background

Safety of marine operations is significantly important as it prevents unexpected down time, reduces the number of accidents and also helps extend the life of structures. For the maritime industry, governmental bodies and classification societies issue guidelines for regulation of the design, operation and maintenance of ships and offshore structures. These regulations provide a reliable safety level for all parties over the lifetime of the structures. However, over the past few decades several catastrophic accidents have occurred around the world due to failure in the operation of marine systems. These devastating failure events require special attention to be given to investigating advanced risk and reliability framework for alleviating human loss and improving the safety of marine operations. The reason for this being that marine accidents may pose various major risks in terms of environmental pollution and loss of assets for companies. In the majority of cases, marine accidents may also cause human casualties. Therefore, it is necessary to take into account the process of risk escalation in a more realistic way rather than relying only on either precursor data or expert judgments. When it comes to accident modelling and risk analysis of marine floating systems, a systematic approach is required. To achieve this objective, the marine community is interested in performance-based reliability assessment and on line risk assessment which take into account the entire lifetime of the system or the structure, (Friis-Hansen, 2000). Performance means the ability of the system to operate under the given conditions. Performance based studies are directly dependent on predictions of magnitude and frequency of occurrence of accidental loads, i.e. on the risk associated with operating the system. The associated risks are influenced by many factors, each involving a great number of uncertainties. Despite these uncertainties, the decision making on how the structure should be designed, operated or maintained in an environmental condition play an imperative part in taking optimum action and mitigating the risk of failure.

Due to irregularities in the sea conditions, it is also necessary to evaluate the nonlinear dynamics of a floating system to develop a reliable measure of safety. Catastrophic hurricanes such as Ivan, Katrina and Rita in the Gulf of Mexico indicate that the impacts of extreme environment on assets are extremely destructive and result in considerable human loss and financial detriment. A large number of marine accidents, including the Mediterranean Sea migrant shipwreck and the Demas Victory, a Dubai-based supply ship, have occurred due to a harsh environment with extreme response of vessels encountering rough sea waves, (Townsend 2015). Another example is that the majority of of all large Greek vessel accidents from 1992 to 2005 were due to grounding (Samuelides et al. 2009). The critical questions then are how to minimize the risk of failure, how to improve the reliabity of an operation over time, and how to manage the accident situation by making an optimum decision to remove the catastrophic situation? Most of the existing risk assessment models are based on historical data obtained from previous marine accidents, and thus they can be considered reactive instead of proactive (Montewka et al. 2014). It is essential to establish a proactive framework that can evalute performance of the structure under extreme loads to estimate the risk of marine accident with regard to risk escalation based on proactive approaches. This motivation can be the reason to investigate the causality of possible accident scenarios in a harsh marine environment by means of advanced probabilistic modelling. For this purpose, it is essential to integrate the recent approaches of nonlinear dynamic analysis of floating structures with advanced probabilistic models to develop a strong risk assessment tool for improving the safety of marine operations in a harsh environment. Although there are a number of methods for reliability assessment of marine structures, Bayesian statistic is one of the methods recommended by Sørensen (2004). An extensive review of Bayesian approach and probabilistic tools, including a wide range of their applications, are provided by (Nielsen, 2009). Bayesian approach is regarded as a promising tool that allows reflection of available knowledge on the considered stochastic process (Groth et al. 2010; Khakzad et al. 2011; Montewka et al. 2014; Musharraf et al. 2014; Trucco et al. 2008, Abaei et al. 2017, Abaei et al. 2018a, Abaei et al. 2018c, Abaei et al. 2018d). It is also capable of considering continuous variables in a discrete format (Friis-Hansen 2000, Straub 2009) and conducting the inference of more complicated stochastic relationships among random variables in the network.

These applications demonstrate the importance of accident modelling and reliability estimation of any process facilities and engineering operations. However, investigating more realistic and robust frameworks in marine operations has not received enough attention. Furthermore, it is also highly necessary for maritime authorities to simulate the real condition of marine accidents to improve their prediction tools for associated failures and decision making scenarios. It is still challenging to model reliability of marine operations in more complicated schemes which requires further research.

In this research Bayesian approach is integrated with hydrodynamic modelling of the marine structure to investigate performance and to develop several novel methodologies and tools to evaluate the safety of marine operations. The methodologies and tools developed in this PhD study can be applied to marine operations on any ship and offshore structure.

1.2 Research Objectives and Research Questions

The primary objective of this PhD thesis is to develop advanced probability model and risk based decision making support tools that enhance safety and reliability of marine operations. This is addressed through the following objectives:

- to develop a framework for integrating advanced reliability engineering with hydrodynamic analysis of marine structures;
- to develop an optimum wave train function for modelling storms that assists in evaluating hydrodynamic performance of the structure in a harsh environment;
- to develop a risk based methodology that improves the safety and reliability of marine structures during a storm condition;
- to develop a decision making framework to assist in taking prompt action at different levels when encountering storm;
- to develop an accurate reliability framework for predicting grounding failure of a vessel transiting a shallow waterway, and;
- to develop a dynamic human reliability methodology for improving safety of marine operations in a harsh environment

Moreover, each objective is accomplished by answering a relevant research question. These questions are recorded below:

- How to propose an integrated reliability assessment technique, in particular for estimating reliability of marine operations?
- How to develop a risk-based technique to model the uncertainty of the extreme response of the structure in a harsh environment?
- How to determine the optimum decision for an individual on board while the structure encountering storm;
- How to predict the expected time of grounding failure for a vessel cruising shallow water?
- How to develop a human error assessment technique with considering the effect of time on the endurance of human performance?

1.3 Scope and Limitations

The focus of this PhD study is to develop new methodologies and tools for risk and reliability assessment of marine operations. The presented frameworks are developed based on the hydrodynamic analysis of marine and offshore structures to generate the necessary data for modelling reliability of the operations. The scope of this research is firstly to improve reliability of the marine structures by integrating new technologies in probability modelling and hydrodynamic analysis of the structures. Secondly it is to investigate the performance of marine structures subjected to the storm by developing a tool that represents different intensifying levels of random waves encountered. Thirdly, it is to evaluate reliability of a vessel transiting shallow water to mitigate the risk of grounding failure. Finally, it is to develop a dynamic reliability tool to predict human error considering the effect of time on performance in a phase of marine operations. The first methodology is developed by proposing a framework to conduct reliability analysis of moored floating structures using BN. This study explains how the hydrodynamic and reliability analysis could be integrated with BN to assess the overall safety of offshore structures. The extreme responses of a structure are estimated using analytical frequency domain method, while mooring failure probability is estimated using limit state function in the proposed BN framework. Application of the methodology is demonstrated by estimating the failure probabilities of a floating cylinder with tensioned mooring system. The methodology presented can be employed to mitigate associated risk with marine structures that are affected by stochastic hydrodynamic loads. The second framework is developed to evaluate the hydrodynamic performance of the structure in extreme conditions such as a storm. In this study, a novel numerical model of a storm is developed based on Endurance Wave Analysis (EWA) concept. The proposed method is computationally time efficient and is more realistic in analysing the dynamic behaviour of a structure by separately replicating each level of storm. This method is applied to a Floating Storage Unit (FSU) to evaluate the responses of the structure during a storm in the North Sea. The proposed method is beneficial for future risk and reliability analyses that require a great deal of data. Therefore, the third framework is developed to effectively model a risk assessment tool for safety analysis of marine structures under storm conditions. This part of the study introduces a proactive framework to utilize the critical stochastic variables directly from the hydrodynamic analysis of the floating structure instead of relying on expert judgment or precursor data. For this purpose, a novel numerical model is proposed to replicate a storm based on EWA method. The critical stochastic variables are subsequently used in BN and consequently in ID to develop the risk based decision making model. The application of the methodology is demonstrated through an FSU experiencing a capsizing scenario. The integrated methodology assists in better understanding of accident events and associated risk under different operational conditions. In the fourth step, a novel probability model is developed to predict grounding failure of a large vessel transiting shallow water. The application of the methodology applied to investigate a large vessel cruising shallow coastal waters in Queensland, Australia. The proposed method is useful to estimate more accurately the reliability of vessels transiting shallow water to minimize the risk of touching the seabed.

Finally, the fifth methodology is developed to estimate human fatigue during marine operations encountering a harsh environment. The proposed approach considered the uncertainties over the time of the operation to predict more precisely human reliability considering a hydrodynamic analysis of the structure along with a subjective analysis of human activities in different weather conditions. Subsequently, to evaluate the effect of time on human performance during the operation, a model based on Dynamic

Bayesian approach is developed. The framework will be able to improve the safety of human life in marine operations by predicting the reliable endurance time of human performance in a specific operation.

The methodologies and tools in this study are not developed for a particular ship type nor size, and these methodologies and tools are applicable to any types of structure. In order to generate the necessary hydrodynamic response data with respect to performing risk and reliability assessment, it depends on the proposed problem to choose a proper method for estimating hydrodynamic loads and developing an appropriate probability model that can describe the uncertainties involved in the problem. In addition, the developed frameworks in this thesis are considered neither as an in site condition monitoring nor as experimental tests for evaluating performance of the structure. The generated data only rely on modelling the physics of the failure using commercial software. The content of the thesis only considers different types of methodology for a particular failure modelling of the critical accident scenario in marine operations of each study. It does not pay attention to fault diagnosis and fault detection involved in marine operations. The probability tools adopted in this thesis only rely on Bayesian Inference and no other machine learning tools are applied for comparing the results or examining the advantages of the method with respect to other advanced probability models. However, a wide literature review has been conducted to demonstrate the capability of the considered probability tools in this study.   The frameworks developed in this PhD research can assist in mitigating the associated risk of marine accident during the operation to improve the safety of marine structures and human life.

1.4 Organization of the thesis

This thesis is written in manuscript format (paper-based). Marine risk and reliability assessment is a necessary field of study for improving the safety of the operation and the life time of the structures. Considering this fact, more precise frameworks are needs to be developed that can assist industries to monitor reliability of their system more systematically by adopting specific tools. These tools should then include all imperative points of view from hydrodynamic modelling to advanced probability models which are definitely a basis for reliability study of marine systems. Therefore comprehensive and informative links between the chapters of this thesis are considered for highlighting the risk and reliability context in the field of marine engineering and the expected tool characteristics. As a result, when first looking at the problem, a methodology was developed as an entry for incorporating hydrodynamic modelling with enhanced machine learning tools. Later, different two step frameworks were designed to monitor either performance of the vessel or human performance in a harsh environment such as encountering storm. Related to each study a proper systematic probability model was then constructed to predict reliability of the structure or the human behaviour operating on a system. Finally, in each study, imperative notes relating to the problem was then presented clarifying the advantages of the developed frameworks on improving reliability of the marine systems and of human performance. A general overview of these links are further illustrated in Figure 1.1.

Lack of integrated reliability model (Chapter 2, 4, 5)	**Lack of decision making tool in harsh environment (Chapter 3, 4, 6)**	**Lack of a time dependent reliability model (Chapter 4, 5, 6)**
• Improving uncertainty modelling • Integrating hydrodynamic modelling and advanced probability models in a unified approach	• Developing a more realistic storm condition • Developing a support decision making tool considering the storm effect of the structures and human performance	• Considering the nonlinearity in hydrodynamic modelling and prediction tool • Developing a time domain model using non-linear process for predicting reliability of the system

Figure 1.1 A general overview of the link between chapters of the conducted research in this thesis

A summary of the thesis outline is provided in the section below. To a large extent these chapters are independent and can be read individually.

Chapter 2: Reliability Assessment of Marine Floating Structures Using Bayesian Network

This chapter presents the development of a comprehensive methodology to assess the reliability analysis of moored floating structures using BN. The developed methodology is applied to a floating cylinder with a tensioned mooring system as a case study. The integration of the hydrodynamic and reliability analysis based on BN is described for assessing the overall safety of the offshore structures

Chapter 3: A Novel Approach to Safety Analysis of Floating Structures Experiencing Storm

Chapter 3 explores the development of a novel approach for simulating storm conditions for evaluation performance of a marine structure in a harsh environment. The approach has the capability to be applied for critical analysis of a marine structure subjected to a storm. It is also helpful for future risk and reliability analysis to evaluate safety of the marine structure in a harsh environment.

Chapter 4: A Robust Risk Assessment Methodology for Safety Analysis of Marine Structures under Storm Conditions

Chapter 4 proposes a risk based decision making tool based on using BN and Influence Diagram (ID) for safety analysis of a marine structure. The methodology assists in better understanding accident causation and associated risk in changing operational conditions when taking optimum action in a failure event such as a capsizing vessel. The framework is an effective tool for quick and robust risk assessment by incorporating the uncertainty associated with the dynamic behaviour of a floating structure and the stochastic nature of operational and marine structure response variables.

Chapter 5: Dynamic Reliability Assessment of Ship Grounding Using Bayesian Inference

Chapter 5 provides a reliability assessment framework for advanced grounding failure modelling of a vessel transiting shallow water. The developed methodology can be applied by designers, operators and port managers to maintain their shipping fleets operating at an acceptable level of grounding safety. The framework suggests optimum vessel speed for a safe navigation in different environment conditions to minimize the risk of grounding failure.

Chapter 6: A Dynamic Human Reliability Model for Marine and Offshore Operations in Harsh Environment

Chapter 6 investigates human performance and related uncertainties over the time of the marine operation to estimate an accurate human reliability assessment. A model based on Dynamic Bayesian approach is developed to evaluate human fatigue by considering the effect of operational time on human behaviour. The model considers the uncertainty of human performance shaping factors by adopting a hydrodynamic analysis of the structure along with a subjective analysis of human activities in different weather conditions. The outcome of this study is to alleviate the safety of human life in marine operations.

Chapter 7: Conclusions

The final chapter summarizes the major findings of this PhD study and points to several new directions for future research.

2. Reliability Assessment of Marine Floating Structures Using Bayesian Network

Abstract

Marine floating structures are widely used in various fields of industry from oil and gas to renewable energy. The predominant dynamic responses of these structures are controlled by mooring lines. In recent years, a number of high-profile mooring failures have highlighted the high risk of this element in floating structures. A reliable design of mooring liness is necessary to improve the safety of offshore operations. This paper proposes a novel methodology to conduct reliability analysis of moored floating structures using Bayesian network (BN). The long-term distributions of extreme responses of the floating object are estimated using analytical frequency domain method, while mooring failure probability is estimated using limit state function in the proposed BN framework. Application of the methodology is demonstrated by estimating the failure probabilities of a floating cylinder with tensioned mooring system. The proposed study also explains how the hydrodynamic and reliability analysis could be integrated with BN to assess the overall safety of the offshore structures. The methodology presented can be employed to mitigate associated risk with marine structures brought about by stochastic hydrodynamic loads.

Keywords: Bayesian Network, Reliability, Hydrodynamics, Floating Structures, Mooring System

2.1 Introduction

Marine floating structures are widely used in the oil and gas industry, marine transportation and exploration areas and renewable energy applications. Conceptual design scenarios for each of these structures are based on environmental loads such as wave, wind and currents. Due to the stochastic behaviour of the sea environment, different types of failures are expected to occur, however it is necessary to improve the safety of marine structures during their lifetime. In the past few years, there has been an increasing focus on analysis of the extreme loads on oil and gas platforms (Hennig 2005; Kim and Zhang 2009; Padgett et al. 2012). To explain the complexity of the problem and the various factors involved in the field of marine engineering, a review of marine reliability analysis adopted from previous research is schematically illustrated in Figure 2.1.

Previously, in order to conduct mooring failure analysis, traditional reliability methods were applied, such as the first order reliability method (*FORM*) and second order reliability method (*SORM*) applied by Gao (2008) and Frosing and Jansson (2013). Siddiqui and Ahmad (2000) suggest that failure probability of a mooring system may increase when one mooring system has to be replaced or repaired due to partial or complete damage. With emphasis on the importance of progressive failure, or the entire collapse of the floating system, they investigated reliability of the mooring system of a Tension Leg Platform (*TLP*). Li et al. (2005) analysed the effect of downstroke on the reliability of tendon unlatching using FORM and SORM, rather than considering the loss of tendon tension.

Although there are a number of methods in the literature for reliability analysis of marine structures, Bayesian statistics is recommended by Sørensen (2004). An extensive review of BN and probabilistic tools including a wide range of BN applications are provided by (Nielsen, 2009). Among the current probabilistic models for risk and reliability analysis, Bayesian approach is a promising tool that allows reflection of available knowledge on the process being analyzed (Groth et al. 2010; Khakzad et al. 2011; Montewka et al. 2014; Musharraf et al. 2014; Trucco et al. 2008, Abaei et al. (2017)). Since Bayesian approaches are capable of considering continuous variables in a discrete format (Abaei et al. 2018a, Friis-Hansen 2000, Straub 2009), it is possible to conduct the inference of more complicated stochastic relationships among random variables in the network, i.e. each variable may have more values than true or false (such as different level of storm conditions), and not all the dependencies have to be deterministic (such as utilities for decision making). In comparison, other probabilistic models such as FORM and SORM, are not well suited to conduct risk and reliability analysis efficiently (Friis-Hansen 2000). Recent research has applied BN to engineering fields such as corrosion on steel structure and condition monitoring (Luque et al. 2014; Spackova and Straub 2015; Straub 2009). Wang, (2011) used Object Oriented Bayesian Network (OOBN) to investigate the failure probability of different types of Australian bridges in terms of both structural reliability and conditional-based reliability. Morales-Napoles et al. (2012) applied BN as a tool for assessing the failure risk of earth dams providing a conceptual framework for implementation of continuous stochastic variables in BN.

While the application of BN in reliability analysis of marine application is shown by previous researchers (Friis-Hansen 2000; Nielsen and Sørensen 2010; Sørensen and Toft 2010; Straub 2004, Abaei, et al. 2017, Abaei, et al. 2018a), it is still necessary to integrate the probabilistic and hydrodynamic analysis of marine floating structures for risk assessment purpose. The risk assessment of systems or components such as moorings requires a probabilistic damage model or inspection and monitoring database. Referring to previous studies, BN is a promising and efficient approach in the conduct of reliability analysis compared to the traditional method developed by Vazquez-Hernandez et al. (2006), Montes-Iturrizaga et al. (2007) and Vázquez-Hernández et al. (2011). In this study, a new methodology for assessing the reliability of floating offshore structures using BN and frequency domain analysis is developed. The strength of the framework is its computational efficiency when performing Bayesian updating integrated with hydrodynamic response of the structure for estimating reliability of the operation and determining optimum design point of critical components such as mooring lines. To demonstrate the application of the developed methodology, a floating renewable energy substructure with tensioned mooring is considered as the case study. A limit state function for critical surge response is derived analytically based on the Potential theory and Hooke's law. The response based stochastic variables induced by hydrodynamic wave forces are computed for various sea states. The aim of this study is to argue an interpretation of using *BN* for marine structural reliability analysis in terms of extreme condition scenario and allocate it as a tool for future research on interdisciplinary study for structural reliability analysis, system failure detection, human error estimation and decision making. This will enable the risk assessment to improve the safety of the offshore structures' operation during their lifetime. The framework enables robust reliability updating for determining the best design point of the maximum excursion in the mooring line. By robust it is understood that the reliability updating can be performed in an automated manner using the developed BN. That is, the performance of the structure itself is employed to estimating the reliability of the structure that encounters sea environments such as wave components. In brief, the conceptual framework, the scope of the study in each section of Environment, Hydrodynamics, Reliability and Failure model is shown in Figure 2.1. The highlighted box in the figure represents a figurative description of different steps that are considered in this paper to integrate Bayesian Network and Hydrodynamic of marine floating structures. For example, the "Potential Fluid" Box means that Potential theory is applied to investigate the hydrodynamic response of the structure, and "Mooring Failure" is highlighted as a failure model for this study. Additionally, each hierarchical diagram in this figure represents the previous research conducted to improve the reliability of the marine structures.

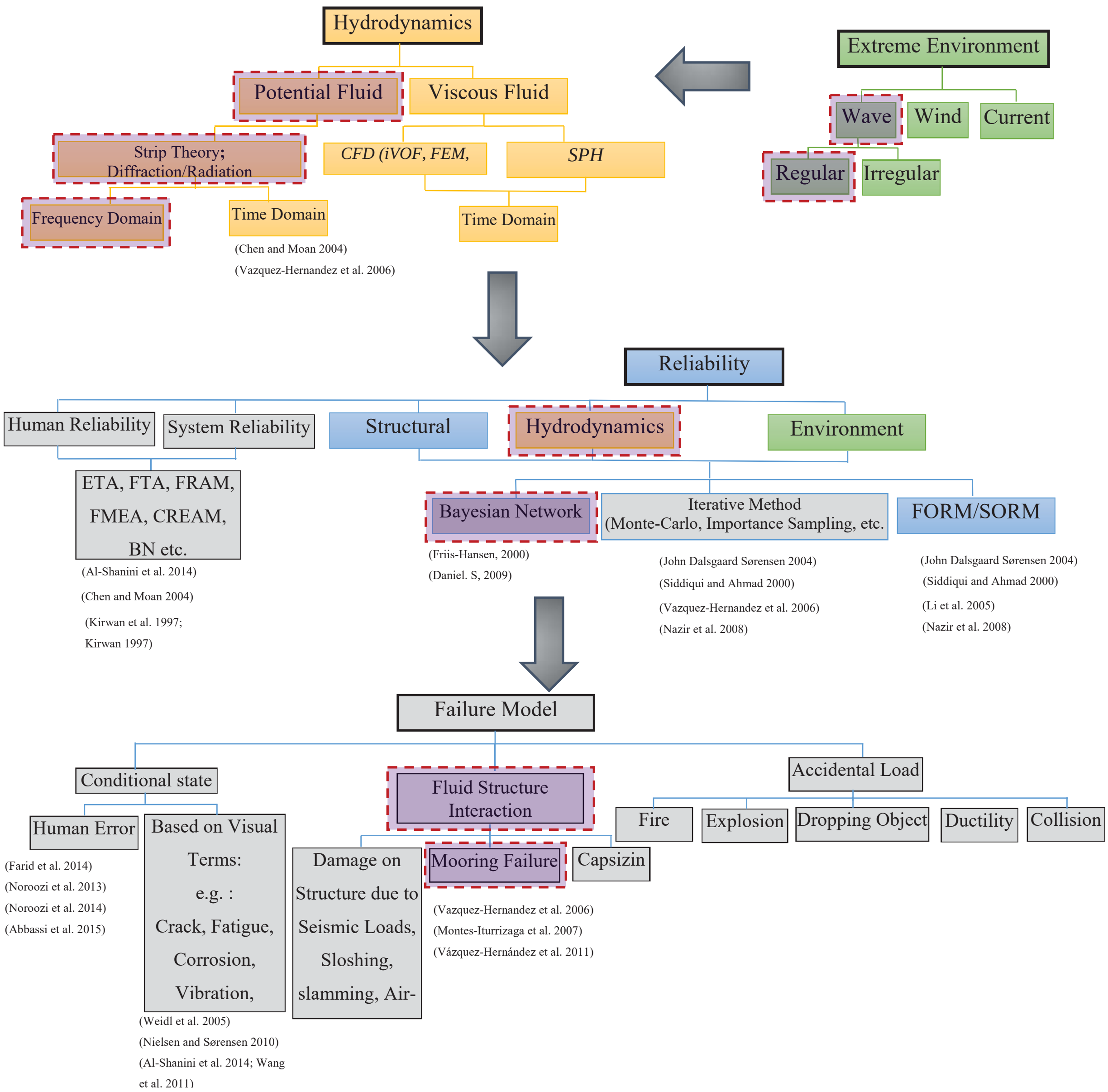


Figure 2.1 Accident modeling framework applied to marine environment.

2.2 Developed Methodology

During the conceptual design phase, it is necessary to find an efficient approach for estimating probability of failures to be used for safety analysis of marine structures. A comprehensive probabilistic study of different phenomena in marine structures hydrodynamic aspect of the design are requisite for the development of any risk mitigation strategies. With this objective, it is necessary to precisely estimate the occurrence of the long-term response of the structures describing them probabilistically to account for uncertainties. In this study, an integrated methodology is developed based on frequency domain analysis along with Bayesian network for hydrodynamic and structural reliability analysis respectively. The methodology is divided into five steps. Firstly, the long term probability distribution of sea waves is estimated. Secondly, for each significant wave height, Hs, Pierson-Moskowitz spectrum is considered to calculate the wave force and response of the structure. Wave forces are computed based on frequency domain method determining response amplitude operator (RAO). In the third step, the response spectrum is used to estimate the expected value of surge response. Rayleigh distribution was applied to evaluate the highest 1% of the responses, $\bar{X}_{0.01}$, for each spectrum. This distribution is the most suitable probability density function to predict the maximum response in different sea states (Kamphuis 2010). The major causes of failure in floating structures are the responses of the structure due to extreme loads. It is necessary to predict the highest possible responses that structure encounters, i.e. determining the best design point. In this study, mooring disconnection was considered as the failure scenario. Expected value and standard deviation of $\bar{X}_{0.01}$ responses are fitted to a Gumbel distribution to model the long term performance of a floating structure. Other related design parameters such as the elasticity and strength of materials are assumed to have a normal distribution. This is a valid assumption as it has previously been considered by several researchers (Friis-Hansen 2000; Kamphuis 2000). Geometric variables such as the mooring and object diameter, and length of mooring line are defined as deterministic values. In the fourth step, a suitable limit state function was developed to model the failure of the mooring system. Lastly, to implement the structural reliability analysis, the failure function is mapped into a BN. The network assists in predicting the probability of failure identifying the best design points for the structure. The steps of the developed methodology are illustrated in Figure 2.2.

2.3 Hydrodynamic Analysis (Steps 1)

In this study, a tension cylinder is considered for assessing the reliability of the mooring system. To replicate the environmental loads, a three-parameters Weibull distribution explained in Eq. (2.1), and recommended by Karadeniz et al. (1983), Siddiqui and Ahmad (2000), is used to model the long term probability distribution of significant wave heights:

$$f(H_s) = \frac{C}{B}\left(\frac{H_s - A}{B}\right)^{C-1} e^{-(H_s - A/B)^C} \tag{2.1}$$

where A is the location parameter, and B and C are the scale and shape parameters of the Weibull distribution. These parameters need to be obtained from the scatter diagram of any sea location. In the present paper, sea state data are adopted from a study by Siddiqui and Ahmad (2000) based on the North Sea location, to estimate the long-term occurrence probability of the extreme wave height. According to Siddiqui and Ahmad (2000), corresponding to a known significant wave height H_S, zero crossing period T_Z can be obtained assuming the same probability of occurrence for T_Z as H_S. That is, to consider the long term probability of wave period, the wave height and period (Hs, Tz) are taken in a correlated fashion as per an empirical relation defined as:

$$T_Z = \sqrt{\left(\frac{32\pi H_s}{g}\right)} \tag{2.2}$$

The frequency domain method is applied for predicting extreme responses with regards to each sea state. The structure encounters a wide range of wave heights and wave periods. The wavelength, λ, is assumed to be 5 times larger than the diameter of the structure, so that the diffraction problem is neglected. Using strip theory, the added mass coefficient is derived analytically. Mooring line stiffness coefficient is defined based on Hooke's law. The dynamic equation computed is using frequency domain method to find the response amplitude operator (RAO). In this study, hydrodynamic loads on the structure are computed analytically using frequency domain method. Frequency domain method is extremely fast for computing hydrodynamic loads and is therefore suitable to integrate with reliability analysis of marine floating structures (Karimirad and Moan 2013). To conduct linear stochastic analysis, there is no significant difference between using strip theory or Morison equation for the consumption time of numerical calculation. However, in this study, the hydrodynamic loads have been computed analytically based on strip theory for slender body as presented by Abaiee, et. al, (2015).The stochastic dynamic analysis of the structure is performed for 12 sea states then referring to the i^{th} sea state, H_S^i (significant wave height of the i^{th} spectrum) and T_P^i (Peak period of the i^{th} spectrum), the 1% of highest response value is computed to predict extreme value responses. To compute the highest 1% of surge motions, a linear stochastic analysis of the structure is performed with the assumption that the wave heights and response followed Rayleigh distribution. The extreme value of the linear response for the highest 1% calculated is based on the exceedance probabilities. Therefore, all ranges of wave height and wave period are considered in this approach to predict the reliability of the structure.

To compute the wave forces on the structure, it is assumed that the fluid is incompressible, irrational and non-viscous (Fuchs and MacCamy, 1953). Therefore, the linear potential theory is applied to model wave velocity for deep water. The model is a linear wave-structure-interaction problem to obtain response of the system in different sea state. Therefore, a linear stochastic approach is considered to evaluate the hydrodynamic response of the structure, since the main objective of this study is to demonstrate a framework to assess the reliability of marine structures using Bayesian Approach with integrating hydrodynamics. To demonstrate the application of the developed methodology, a tensioned cylinder is considered for integrating the hydrodynamic analysis of the structure with the proposed probability model which is discussed in the next section. As suggested by Abaiee (2015), surge and roll motions, among 6 DOFs, are the most critical responses that play a major role in exerting significant tension on the mooring line. Therefore the dynamic equation for the coupled degrees of surge and roll motion are adopted from recent study conducted by Abaiee et al. (2015) and defined as:

$$(m+m_{11})\ddot{X}_1 + c_1\dot{X}_1 + k_{11}X_1 = F_{11}(t) \tag{2.3}$$

$$(I + m_{12})\ddot{X}_2 + c_2\dot{X}_2 + k_{12}X_2 = F_{12}(t) \tag{2.4}$$

where m_{11} and m_{12} are added mass, k_{11} and k_{12} are the stiffness coefficients, $F_{11}(t)$ and $F_{12}(t)$ are wave forces, m and I are mass components of surge and coupled roll respectively. As suggested by Abaiee et al. (2015), the hydrodynamic damping coefficient (c1 and c2) has less importance and can be neglected for this structure. A detailed discussion on the analytical solution of the dynamic equation and the parameters are provided by Abaiee et al. (2015)

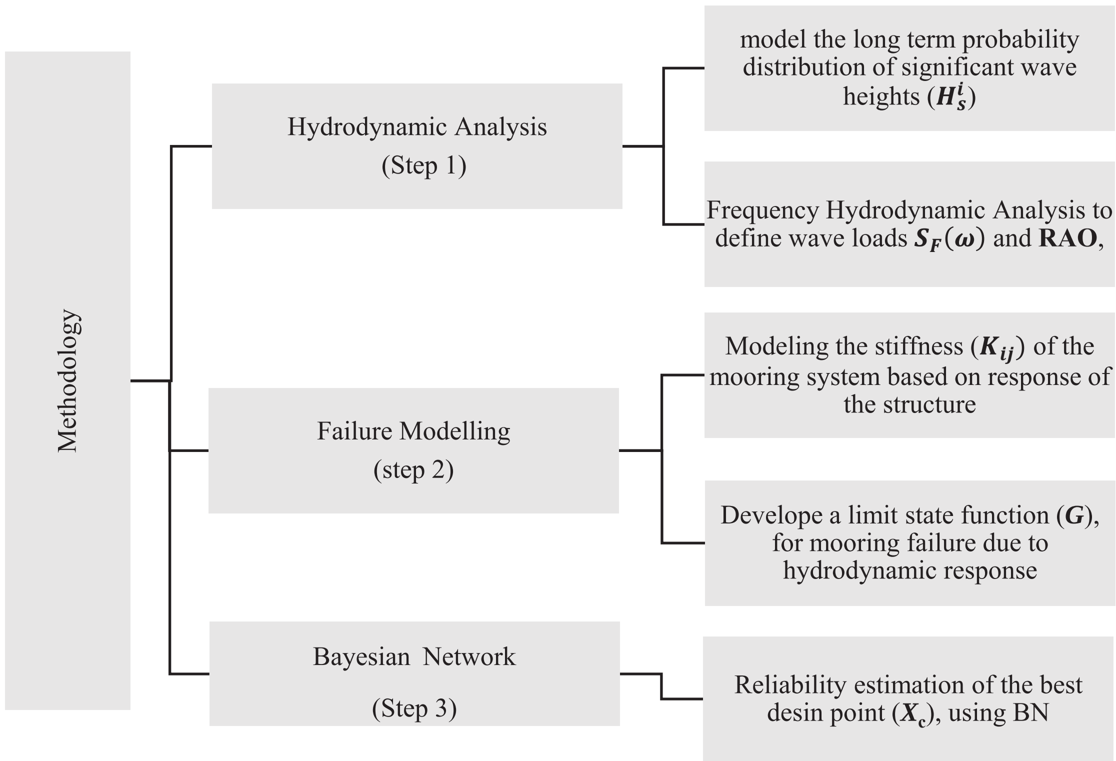


Figure 2.2 Overview of developed methodology for reliability assessment of marine floating structures.

2.4 Failure Modelling (Step 2)

In this study, mooring rupture is considered as a failure mode. It is assumed that if the axial tension exceeds the allowable yield stress caused by the large response of the structure in a harsh environment, then the rupture will occur in the mooring line. The mooring force incurred by environmental load is modelled by Hooke's Law assumption and the maximum surge response as recommended by (Shoghi and Tabeshpour 2014). All variables that are implemented to derive the failure function are presented in Table 2.1 along with the specified probability distribution function. It is essential to determine the most realistic random variable distributions for tendon characteristic. The reason being that during the lifetime of the floating object, the material properties of the mooring lines, as well as its geometry, may change. As recommended by DNV-OS-C105 (2008) for tensioned floating structures, Tendon Tension Monitoring System ($TTMS$) should be installed to obtain the actual tension during the operation. This requires suitable and reliable tendon tension monitoring devices and a precise monitoring program. However, condition monitoring for equipment such as renewable energy systems is not applicable, since most of these new devices have yet to be installed. Any changes in material of tendon, leads to changes in the natural frequency of the system which is an important parameter in damage detection. However, in this study it is assumed that these characteristics have normal distribution as recommended by Kamphuis (2000), and it has a value lower than the mean value. As a result, its normal standard parameter, Z, has a negative amount. Fundamentally, the mooring failure depends on hydrodynamic parameters (surge response, x_{11}, wave height, H_s, Wave period, T_z), material characteristics (elasticity, E, yield strength, σ_v), the geometry (Cross section, A, Length of mooring, L) and the pre-tension, T_0. The relationship between these variables is modelled by introducing a suitable failure function defined as $G(x_{11}, H_s, T_Z, E, T_0, A, L, \sigma_v)$.

Table 2.1 Stochastic variables considered in hydrodynamic analysis

Variable		Distribution	
x_{11}	Surge response	Gumbel	$P(X_{11}) = exp\left[exp\left[\frac{-(X_{11}-a)}{b}\right]\right]$
E	Modulus of elasticity	Normal	Z_R= +1.28
T_0	Pre-tension of tendon	Normal	Z_R= +1.28
A	Cross section of tendon	Deterministic	Z_R= 0
L	Length of tendon	Deterministic	Z_R= 0
I	Moment Inertia for Cylinder	Deterministic	Z_R= 0
σ_V	Von-Mises stress (for axial load only)	Normal	Z_R= -1.28*
H_s	Significant wave height	Weibul	Eq. (2.1)

*Z_R is the normal standard deviation and defined as $Z_R = \frac{x-E(x)}{\sigma}$. The number -1.28 means that the random variable is with 0.9 probability lower than its mean value.

The limit state function will determine whether the system is in safe or fail mode. The developed function is:

$$G(F_T(X) > F_T(X_c)) = F_T(X_c) - F_T(X) \tag{2.5}$$

where $F_T(X) = k_{11}X_{11}$ is the tendon force due to surge and roll responses, X_c is the critical surge response that represents a design parameter and is defined as any break or disconnection in tendon, k_{11} is nonlinear stiffness due to the unique hydrodynamic load in surge direction. The inequality $F_T(X) > F_T(X_c)$ shows the limit if the forces on the mooring line, $F_T(X)$ exceed the critical loads, $F_T(X_c)$. The surge force in tendon is linear with respect to the wave height (Faltinsen 1993), then the limit state function defined in Eq. (2.8) is truncated on the mean value of surge response, X_{11}. Since the response of X_{11}^i in long-term is fitted to a Gumbel distribution, the mean value is $E[X_{11}] \neq 0$. The super index i represents i^{th} sea state. The design load, $F_T(X_c)$ is defined according to the flexibility and strength of the material which is based on the design criteria. Mooring force is $F_T(X)$ estimated based on Hooke's linear elastic equation as $F_i = k_{ij}X_i$ in 6 degree of freedom (DOF) (Shoghi and Tabeshpour 2014). K_{ij} is an array of the stiffness matrix defined by applying a unit displacement on the structure in j^{th} direction, equal to the resultant mooring force experienced in i_{th} direction (Shoghi and Tabeshpour 2014). The stiffness coefficient of tendon in surge direction is derived approximately according to the tailored truncated of the left hand side of the equation as (Shoghi and Tabeshpour 2014):

$$\begin{aligned} k_{11}x &= \left(T_0 + \Delta T\right) sin\theta \simeq \\ &= \left(T_0 + \frac{\left(\sqrt{x^2 + L^2} - L\right) AE}{L} \right) sin\theta \\ &= \left(T_0 + \frac{\left(x^2\right) AE}{\left(\sqrt{x^2 + L^2} + L\right) L} \right) sin\theta \\ &\simeq \left(\frac{T_0 x}{L} + \frac{AE}{2L^3} x^3\right) \end{aligned} \tag{2.6}$$

and,

$$k_{12}X_{12} = -(KGX_{11})X_{12} \tag{2.7}$$

where T_0 is the tendon pre-tension, ΔT is the extra tendon tension, θ is the angle between tendon line and its initial vertical position, i.e. $\sin\theta \approx \theta = \frac{x}{L}$. Therefore Eq. (2.8) is truncated over $X_{11} = E[X_{11}]$ to define linear failure function:

$$G \approx F_T(X_c) - \left(\left(\frac{T_0 E[X_{11}]}{L} + \frac{AE}{L} E[X_{11}]^3 \right) + \left(\frac{T_0}{L} + 3\frac{AE}{L} E[X_{11}]^2 \right) \left(X_{11} - E[X_{11}] \right) \right) \ , \ \begin{Bmatrix} if\ G > 0\ ;\ Safe\ Mode \\ if\ G \leq 0\ ;\ Fail\ Mode \end{Bmatrix} \tag{2.8}$$

$$E\left[X_{11}\right] = \sum_{i=1}^{m} f\left(H_s^i\right).\bar{X}_{0.01}^i \tag{2.9}$$

where $\bar{X}_{0.01}$ is the average of highest 1% of structure's linear responses, supposing that the maximum response in each sea state follows a Rayleigh distribution:

$$\overline{X}_{0.01} = 6.67\sigma \tag{2.10}$$

where σ is the standard deviation of structural responses. To find a suitable probability distribution, ($P(X_{11})$ in Table 2.1), for long-term occurrence of structural responses, MLE method is applied to estimate distribution properties such as the shape and scale parameter for each case. When failure due to extreme condition is of interest, (such as extreme surge response in this study), then special attention is needed to predict the parameters that are highly unlikely to occur. In previous studies by Diznab et al., (2014) and Chen and Moan, (2004), it has been recommended that Generalized Extreme Value (GEV) and Gumbel distributions are two of the most suitable distributions for modelling long-term performance of marine floating structures under extreme loads. For this study, Gumbel distribution is considered to correctly predict the stochastic time-response data.

2.5 Probabilistic Analysis: Bayesian Approach (Step 3)

BN is a graphical model for reasoning under uncertainty that uses causal relationships (represented by directed edges) among components of a system (represented by chance nodes). BN estimates the joint probability distribution of a set of random variables based on the conditional independencies and the chain rule, as stated in Eq. (2.14). An extensive review of BN and probabilistic knowledge elicitation including its applications in risk and reliability analysis is provided by Barber (2012), Scutari (2014) and Benson (2015).

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(X_i \mid pa(X_i)) \tag{2.11}$$

where $pa(X_i)$ is the parent set of variable X_i. In case new information becomes available for one or more chance nodes, BN is able to update the joint probability based on the Bayes' theorem:

$$P(X \mid E) = \frac{P(X, E)}{\sum_X P(X, E)} \tag{2.12}$$

This advantage of the BN will be adopted to estimate the optimum design point of the structure's mooring system assisting in failure modelling (see Eq. 2.11). Friis-Hansen (2000) provides a more detailed explanation of BN concepts. The application of BN in the field of risk and reliability is explored by many researchers. A few recent examples include Abaei et al. 2018d, Arzaghi et al. 2017, Abbassi et al., 2016; Bhandari et al., 2016; Yeo et al., 2016. Inserting continuous variables in BN is not an easy task and many approaches have been adopted by previous researchers to develop approximating models, however the approaches are applicable for normally distributed variables. The alternative approach to consider continuous variables in BN is to discretise them into n states with univariate intervals. This method is defined as the univariate discretization given that the states are all mutually exclusive for these n states (Friis-Hansen, 2000). The optimum number of intervals is estimated by compiling different numbers of discretization in the network using GeNIe Software.

2.6 Discretization of the Continuous Variables

In a BN-based reliability model ($X \rightarrow Z \leftarrow Y$), X and Y are continuous nodes with arbitrary probability distributions and Z is deterministically defined by its parent nodes using failure function. The continuous variables are discretized into a set of mutually exclusive states. Univariate discretization scheme and Monte Carlo simulation is used to find the uniform interval and the final probability of failure as recommended by Friis-Hansen (2000) and Daniel (2009). Using the limit state function, each configuration of the stochastic variables will be sampled to define the safety mode of the structural behaviour. The conditional probability distribution of the failure node is computed by sampling the intervals of the parent nodes for all the configurations. For each sample, values "one" and "zero" are assigned to the cases whether the structure is in fail or safe state respectively (Friis-Hansen, 2000). Finally, using Monte Carlo method, the probability of failure for the limit state node will be computed in the network. The numbers of discretization intervals for all the continuous variables considered for reliability analysis are shown in Table 2.2. The rest of the variables such as significant wave height, H_s, sea wave spectrum $S(\omega)$, and wave force spectrum $S_F(\omega)$ are implicitly considered in the failure function and they should not be regarded as the parent nodes in *BN*.

Table 2.2 Discretization of continuous variables in BN model

Continuous Variables	Type of Distributions	Number of discretization intervals	Interval size
σ_v (N/m^2)	Normal	10	2×10^7
T_0 (t)	Normal	9	70
E (N/m^2)	Normal	10	10^9
X_{11}(m)	Gumbel	22	1.0

The network presented in Figure 2.3 shows the probabilistic model for the reliability of tendon. Node G in the figure contains binary variable with two states of "Fail" as G < 0 and "Safe" as G > 0. It then holds the probability of failure due to increasing tendon forces given values of the input variables σ_v, T_0, E and X_{11}. The conditional probability distribution $P(G|\sigma_v, T_0, E, X_{11})$ should be implemented for each of the $10 \times 9 \times 10 \times 22 = 19800$ configuration of parent variables using the failure function (Eq. 2.11). The probability of failure, P(G) is defined by marginalizing the joint distribution of the stochastic variables in the *BN* using *GeNIe* software.

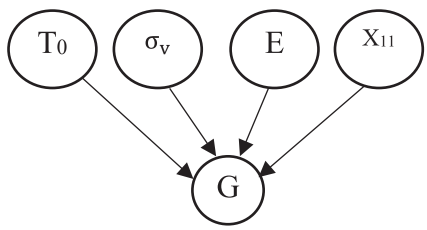


Figure 2.3 Established BN model for assessment of tendon failure.

2.7 Application of Developed Methodology: Case Study

2.7.1 Geometry Details

A floating cylinder is considered as the case study to demonstrate the application of the developed methodology. The structure is connected to a single tensioned line to evaluate the reliability of the mooring system as a result of extreme responses incurred by the wave loads. Figure 2.4 provides a schematic illustration of the structure used in the case study, in which B is centre of buoyancy, G centre of gravity, L is the length of the cylinder, d is the draft, dz, dF and dM are strip elements for vertical deformation, force and moment, respectively, a_{ij} is the added mass in i^{th} direction due to unit deformation of object in j^{th} direction, K is the stiffness of the tendons, E is the modules of elasticity and l is the length of the tether. The stiffness coefficients of tether are defined based on Hooke's law (Shoghi and Tabeshpour 2014). Discretised strip terms for wave force and added mass are presented in Figure 2.4 for two degrees of freedom, surge and roll. All required loads and response variables involved in the case study are presented in Table 2.3.

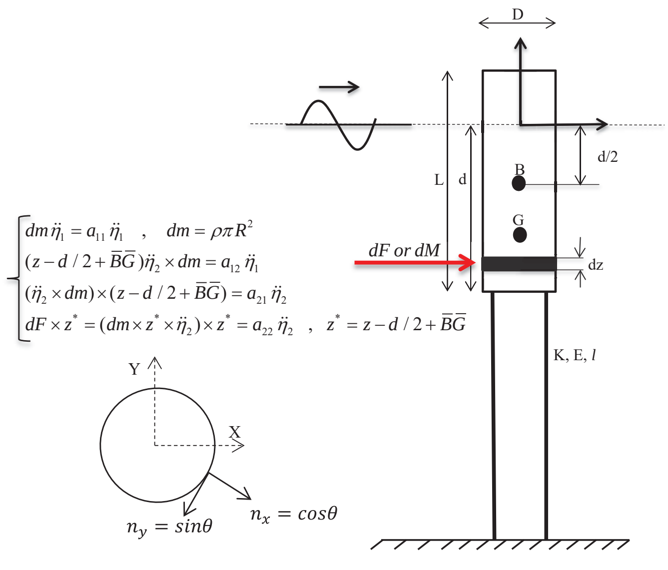


Figure 2.4 Geometry details of a moored floating cylinder considered in the case study.

Table 2.3 Load and response functions derived from frequency domain analysis and Hooke's law for reliability analysis

Load function		Response function	
Surge Frequency Force	$S_{F_{11}}(\omega)=4\rho^2 g^2 A^2 S(\omega)$	Surge Response*	$X_{11}=\frac{1}{\mu_{12}}[(I+m_{12})\omega^2+k_2+\mu_{12}].H_{12}(\omega$
Pitch Frequency Force	$S_{F_{22}}(\omega)=4\rho^2 g^2 A^2 \alpha^2 S(\omega)$	Pitch response due to surge force	$X_{12}=H_{12}(\omega)$
Surge Tendon Stiffness	$k_{11}=\frac{n(\frac{(T_0 x)}{L}+\frac{AE}{Lx^3})}{X_{11}}$	Tendon Force	$k_{11}X_{11}=n\left(\frac{T_0 x}{L}+\frac{AE}{L}x^3\right)$

* $H_{12}(\omega)=\frac{\mu_{12}.2\rho g\pi R^2\xi_a[1-e^{-kd}]}{\Delta}$ called frequency transfer function.

2.8 Hydrodynamic Responses

Physical parameters applied in the hydrodynamic and reliability analysis are illustrated in Table 2.4. Pierson-Moskowitz spectrum density is used to compute the hydrodynamic forces and responses (Kamphuis 2000). The highest 1% of surge responses are derived from each *RAO* to predict extreme value of horizontal excursion of mooring line. The Surge responses spectrum for each sea state are illustrated in Figure 2.5. The probability of occurrence for each significant wave height is selected such that the whole area under cumulative distribution of $\sum f(Hs)\Delta Hs$ equals unity. The product of $f(Hs)\Delta Hs$ then provides the magnitude of the corresponding occurrence probability of the sea state. The final results for the extreme surge response obtained from RAO response of each sea states are reported in Table 2.5.

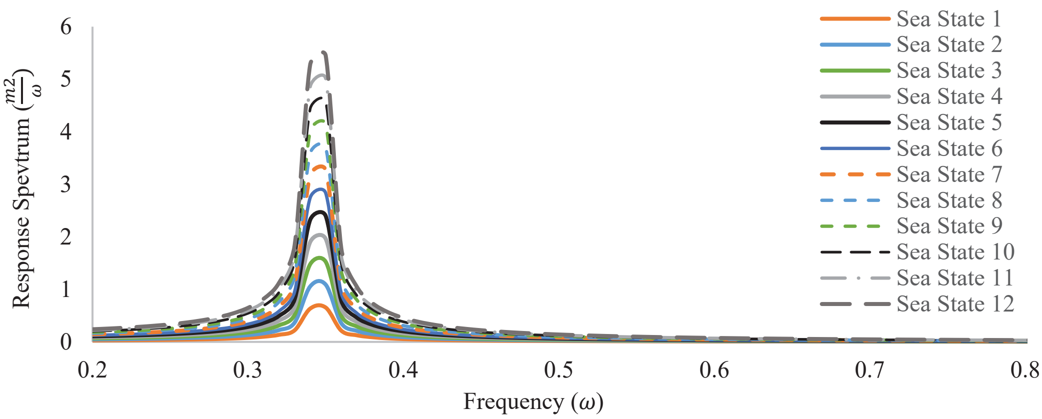


Figure 2.5 Estimated Surge Response Spectrum for of floating structure with respect to different sea states.

Table 2.4 Geometry details of the floating cylinder and its mooring system

Parameters	Value	Parameters	Value
Cylinder Radius (R), m	2	Pre-Tension (T_0), t ($0.7\ \nabla_{Bouyancy}$)	43.96
Water depth, m	50	Module of elasticity (E), GPa	73
Draft (d), m	5	Weight ($0.40T_0$), t	17.58
Height of cylinder (L), m	8	Yield Stress (σ_v), MPa	100
Tendon Diameter, mm	100	Gyration Radius (I), m	0.3 R
KG, m	$\frac{1}{3}$d	GM, m	$\frac{1}{6}$d
Surge added mass (m_{11}), t	62.8	Added inertia (m_{12})	52 t.m

Table 2.5 The highest 1% of the surge responses for each sea state

Sea state Number	Significant Wave Height, H_s (m)	Probability of Occurrence of Wave Height	Standard Deviation for X_{11} (m)	Maximum of Response, $\bar{X}^i_{0.01}$
1	0.75	0.2099	0.0001	0.0008
2	1.25	0.3131	0.0007	0.0048
3	1.75	0.3154	0.0023	0.0158
4	2.25	0.2820	0.0058	0.0387
5	2.75	0.2355	0.0120	0.0801
6	3.25	0.1875	0.0224	0.1495
7	3.75	0.1439	0.0391	0.2614
8	4.25	0.1071	0.0692	0.4616
9	4.75	0.0776	0.1674	1.1165
10	5.25	0.0549	0.4096	2.7323
11	5.75	0.0381	0.8375	5.5864
12	6.25	0.0259	1.4059	9.3776
			Fitted data to Gumbel Distribution of Maxima for Long-Term Surge response	$E[X_{11}] = 0.8539$ $\sigma[X_{11}] = 2.0133$
			Gumbel Parameter	$a = 1.76$ $b = 1.5698$

2.9 Reliability Assessment Results

In this study GeNIe software was employed to conduct the reliability analysis of the mooring system for different critical surge excursion levels, Xc. This parameter represents a condition that the load will start to exceed the allowable design load, and defined as $X_c = \frac{F_T(X_c)}{K_{11}}$. The numerical simulation was performed for 12 different X_C and summarized in Table 2.6. Based on a selected critical surge response in each simulation, the probability of failure estimated correspondingly. In order to determine the best design point, according to the intensity of wave excitation, the strength of mooring profile was increased consistently at each simulation. The simulation performed respectively for all sea states and the associated value captured for plotting in a separated figure. As an example, the numerical result for the case $X_C = 2.4$ m is illustrated in Figure 2.6. The CPT for failure node "G" is completed using Eq. (2.8) and given to the network for estimating probability of failure which is found as $P_f = 5.59E-02$. To define the failure point, node "G" instantiated on "Fail" state. The network is shown in Figure 2.7 and the results are summarized as E=80GPa, T = 490t and σ_v = 100MPa with allowable horizontal surge response of $X_C \leq 2.4$ m. The process continues until the probability of failure reaches a plateau of $P_f = 2.0E-05$ corresponding to the reliability index of β=3.50. Parameter β is defined by a standard normal distribution, Φ corresponding to the reliability of the system in terms of $R = 1 - \Phi(\beta)$ represented in Figure 2.8. It is found that for $X_C > 3.5$ m, the structure will not be affected by extreme waves and probability of failure remains constant at $P_f = 2.0E-05$. That is, for $X_C \leq 3.5$ m, the structure is vulnerable to the sea environment, and otherwise it will be sufficiently flexible due to adequate stiffness of the mooring line in respect to different levels of wave forces. The structure can experience a larger horizontal surge response because of the fact that the mooring line is reliable enough to survive extreme loads. Also, the result confirms that it is well worth keeping the design point as $X_C = 3.5$ m to minimize the cost in designing mooring system. As recommended by Brindley and Comley (2014), there is no necessary rule to demonstrate that increasing the mooring capacity is sufficient to optimize the reliability. Increasing the strength of the mooring line will also escalate manufacturing and maintenance costs. With this objective, this study has investigated the optimum design point resulting in the desired level of structural reliability while it can be regarded as having future cost minimizing strategies.

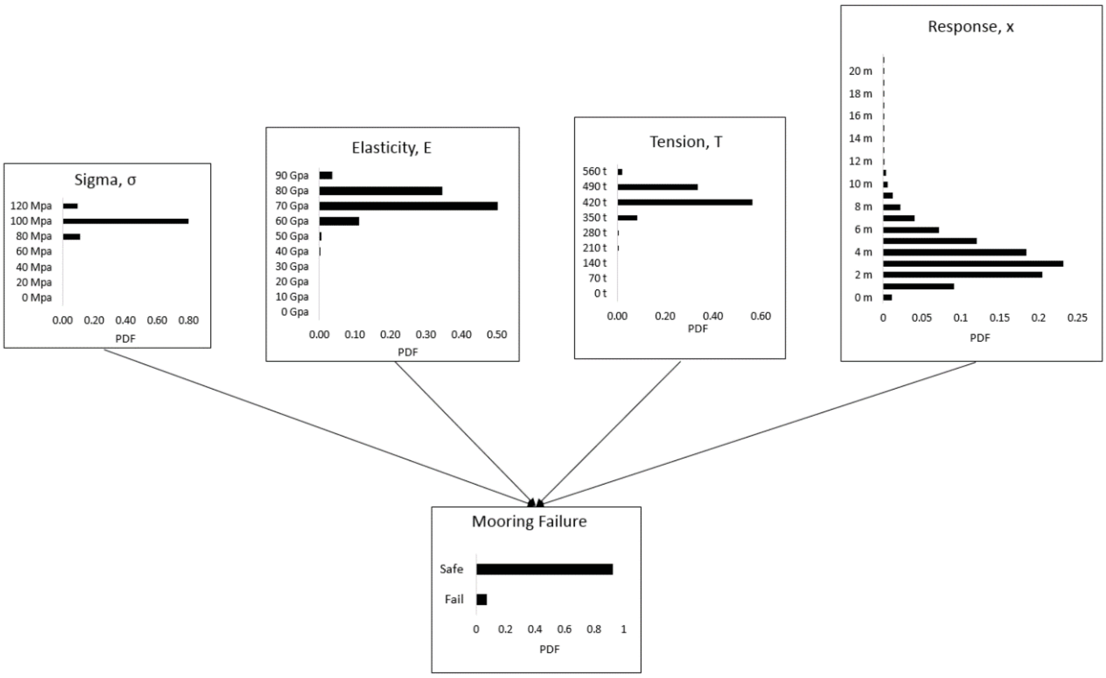


Figure 2.6 Developed BN for reliability analysis of structure (critical surge excursion is considered as $X_c = 2.4\ m$).

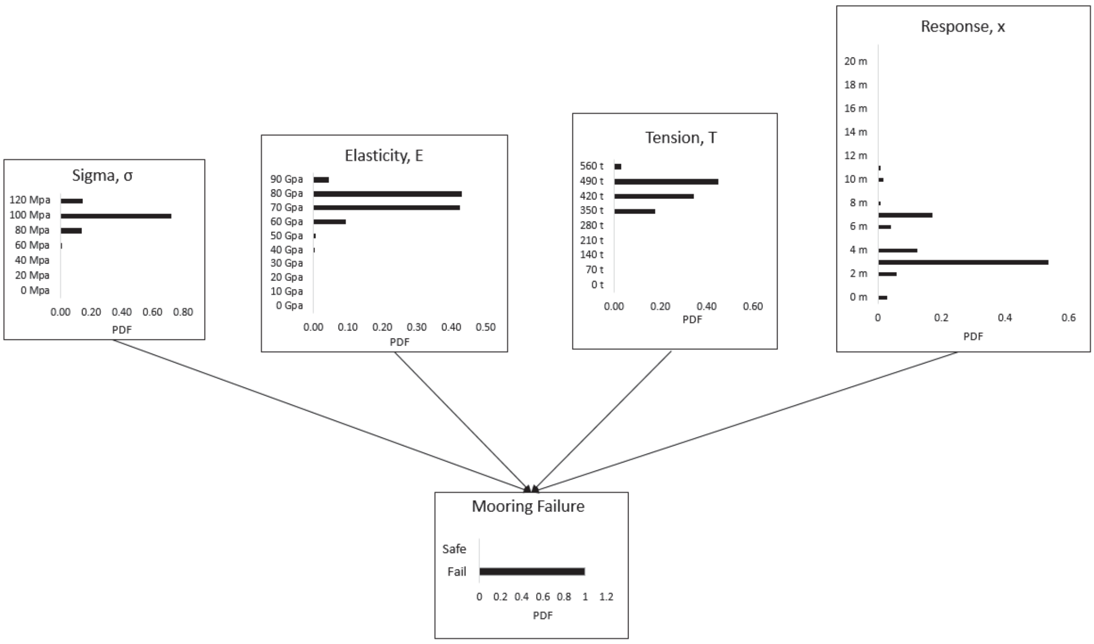


Figure 2.7 Estimation of best design point for critical surge excursion of $X_c = 2.4\ m$.

Table 2.6 Estimated probability of mooring failure obtained from BN model

Maximum allowable critical surge response (m)	Probability of mooring failure
$X_C \le 1.9$	$1.58E-01$
$X_C \le 2.4$	$5.59E-02$
$X_C \le 2.8$	$2.27E-02$
$X_C \le 3.0$	$1.35E-03$
$X_C \le 3.2$	$1.01E-04$
$X_C \le 3.3$	$9.00E-05$
$X_C \le 3.5$	$2.00E-05$
$X_C \le 4.0$	$2.00E-05$
$X_C \le 4.5$	$2.00E-05$
$X_C \le 5.0$	$2.00E-05$
$X_C \le 6.0$	$2.00E-05$
$X_C \le 7.0$	$2.00E-05$

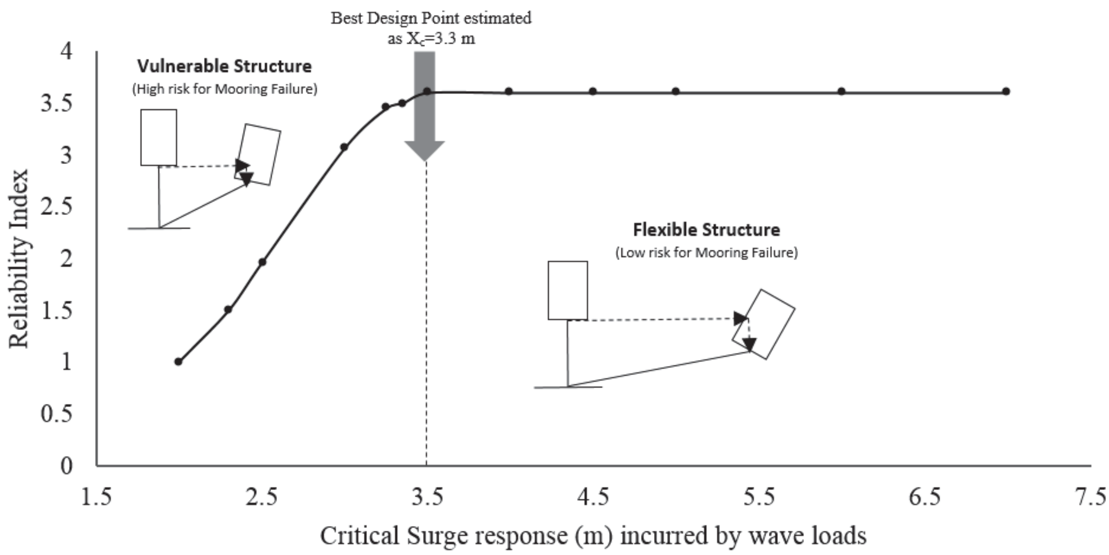


Figure 2.8 Estimated reliability index of different critical surge response considered as the design point

2.10 Conclusion

In this study a methodology is developed to integrate Bayesian approaches with the hydrodynamics of marine floating structures to improve their safety. For this purpose, the frequency domain approach is applied for hydrodynamic analysis given that this method provides an efficient solution to compute either numerically or experimentally the stochastic wave loads on structures. Bayesian network is adopted for estimating the probability of failure to identify the best design point. A floating tensioned cylinder is considered as a case study to demonstrate the application of the methodology. The structure is subjected to 12 sea states and the reliability of the mooring system is examined with respect to the allowable horizontal elongation. It is found that the structure can tolerate the extreme wave height with optimum critical surge response of $X_C = 3.5$ m, corresponding to reliability index of almost β=3.50. This methodology can be applied to effectively perform reliability analysis of a floating structure with tensioned mooring system. In order to use the proposed methodology for another type of failure, firstly it is necessary to develop a suitable limit state function for a particular failure scenario. The same approach should then be followed for developing the BN and estimation probability of the failure .The methodology is capable of being applied for another failure modelling. For this purpose a suitable limit state function, G, for a particular failure scenario (such as capsizing a vessel due to extreme roll angle) should firstly be developed and then follow the same approach proposed in section 2.3 for developing related BN and estimation probability of the failure. Results of this research confirm that the methodology is successful in identifying the critical design point of the system with respect to hydrodynamic response of the structure in different sea states which can assist in maintaining an acceptable level of failure risk during the operational time.

3. A Novel Approach for Performance Analysis of Floating Structure Encountering Storm Conditions

Abstract

A marine floating structure may experience a wide range of harsh environmental conditions during its operational lifetime. It is necessary to evaluate the performance of the structure in extreme conditions such as storm to maintain a desirable level of safety during its operational time. Previously, various approaches were introduced to analyse the response of an offshore structure in different sea states. However, the developed methods are computationally time consuming requiring a large number of simulations. Moreover, it is not the most realistic approach to analyse the dynamic behaviour of a structure by separately replicating each level of storm. In this study, a novel numerical model is developed for modelling storm based on Endurance Wave Analysis (EWA) method. The developed model will reduce the computational cost of simulations to only one storm record of 1100 second and taking into account the random nature of sea environment. The results show that the structure will experience to exceed its survival condition while encountering storm level of 10^{th} in the simulation which is corresponding to the wave height of 12.56m. This will be beneficial for future risk and reliability analysis that require a great deal of data analysis for probabilistic risk assessment. The application of this method is demonstrated through the analysis of a Floating Storage Unit (FSU) responses encountering a storm with varying sea states in North Sea.

Keywords: Safety, survival condition, Hydrodynamics, safety, Reliability,

3.1 Introduction

One of the prerequisites for improving the safety and reliability of offshore structure is to evaluate dynamic behavior of a structure in severe environmental loads such as storm condition, which the structure might become exposed during its lifetime (Abaei et al, 2018d, Arzaghi et al. 2017, Abaei et al. 2017, Bhandari et al. 2016, Bhandari et al. 2015, Diznab et al. 2014; Zeinoddini et al. 2012). Environmental loads, including waves loading, play a dominant role in the design of offshore structures in various stages of construction, transportation, installation and operation (Zeinoddini et al. 2012). Sea waves has a random nature which cause nonlinear forces on the floating structures. Therefore, time-history analysis will become necessary to obtain more accurate results for the structural response during extreme loading conditions. Catastrophic hurricanes such as Ivan, Katrina and Rita in the Gulf of Mexico highlighted the importance of considering the impact of extreme environmental loads on all types of offshore structures. Consequently, there has been an increasing focus on the analysis of extreme waves in the past few years (Cox et al. 2005; Hennig 2005; Kim and Zhang 2009; Wang et al. 2011). Conventional dynamic analysis of marine structure is a time consuming approach as it needs a longer simulation time to generate data for conducting statistical analysis (Agarwal and Manuel 2009). For instance, Chen and Moan (2004) carried out a study with twenty different three-hours simulations to generate time-domain responses. Later, Ren et al. (2015) implemented 84,480 times of one-hour short numerical simulations for investigating the performance of a Spar–Torus-Combination (STC) system. It is therefore necessary to rely on more optimum solutions for dynamic analysis of structure to reduce the large time of simulations. Recently, Endurance Time Analysis (ETA) method is developed by Riahi et al. (2009) and later improved by Riahi and Estekanchi (2010) to reduce the computatioanl cost. The basic concept of this method was first introduced by Estekanchi et al. (2004) in which the structure is exposed to an artificial intensifying acceleration time history. Results of the studies carried out by Estekanchi et al. (2007); Estekanchi et al. (2011); Riahi and Estekanchi (2010) indicate the efficiency and accuracy of this method in the dynamic evaluation of structures subjected to natural disasters such as earthquakes. It should be noted that the principles of structural performance under seismic loads and sea wave excitaions are so-called similar to each other, regardless of the fact that the time duration of storm loads is about several hours compared to seismic loads that take place in a short time (5 to 10 s) (Zeinoddini et al. 2012). According to these differences, Endurance Wave Analysis (EWA) method has beed introduced by Diznab et al. (2014); Jahanmard et al. (2015); Zeinoddini et al. (2012) in order to evaluate nonlinear dynamic analysis of marine floating structures subjected to irregular wave forces.

This paper aims at developing a novel approach for developing storm condition to evaluate performance of marine floating structures. Analysing dynamic behaviour of the structure is the main key point for examining the performance of the vessel in harsh environment. This will clarify that as the structure subjected to the storm, when the behaviour of the vessel will be in safe condition or when it will exceed its survival limit conditions. For this purpose, intensifying dynamic modelling of the structure based on EWA considered for performance analysis of the structure, which develops an extensive range of storm conditions considering the optimum simulation time. In order to illustrate the advantages of the developed methodology, a Floating Storage Unit (FSU) is considered as a real case study. The approach has the capability to be applied for critical analysis of any types of marine structure such as commercial displacement vessels, mooring structures and marine renewable devices, which is subjected to storm. Also, it is helpful for future risk and reliability analysis of these structure for improving safety of the marine structure in harsh environment.

The remainder of this paper is divided into the following sections; **Section 2** explains the concept of EWA for developing different level of storm condition considering only one simulation time. **Section 3** discusses the developed methodology and its elements. **Section 4** presents the application of the methodology in a real case study and **Section 5** highlights the main findings of the present work providing few recommendations for possible future studies.

3.2 Endurance Wave Analysis

The EWA is a simulation-based approach to evaluating the hydrodynamic performance of offshore structures when encountering a wave profile with stepwise increases of wave height. This method that simulates storm conditions is based on the concept adopted from ETA in seismic engineering assisting in reduction of the time required for analysis of marine structures in multiple sea states. In EWA method, different sea states are provided in a single time domain by representing wave spectrum into Intensifying Wave Train Function (IWTF). This function is a relatively short duration time series of the irregular water surface elevation. Zeinoddini et al. (2012) tried to put forward short duration irregular wave time histories, such as Constrained New Wave (CNW) which had no fixed frequency but were delivering a desirable maximum crest height . The final wave train function will then be defined as Intensifying CNW (ICNW). Accordingly, this approach can be adopted for simulating the increasing trend of storms levels over time, which even goes well beyond the design sea state accounting for the random nature of sea waves.

The ICNW wave function is then introduced as a single input of the external excitations for a long-term evaluation of nonlinear dynamic analysis. The performance of the structures and the limit states of failures can be investigated based on the EWA results. The ability of considering spectral features of the sea state and different significant wave heights and frequencies in a single dynamic analysis, taking into account the irregularity and randomness of the sea waves and requiring relatively short simulation time are among the advantages offered by EWA (Zeinoddini et al. 2012). More details on the description of the basics of this concept and progressive analysis methodology for assessment of marine structures under extreme waves can be found in (Diznab et al. 2014; Jahanmard et al. 2015; Zeinoddini et al. 2012).

Figure 3.1 illustrates the three different levels of ICNW profile with different sea states that are adopted for the hydrodynamic simulations of the floating structure. At the beginning, the structure is subjected to a time history wave loading corresponding to a certain significant wave height (Hs) and peak spectral period (Tp) derived from first sea state spectrum ($S_1(w)$). Since the amplitude of the excitation is quite low, the structure remains stable while experiencing this loading (**Case 1**). In the second stage, the significant wave height increases linearly for a same time duration as case 1. At some point during this stage of storm the sturcture will exceed its survival limit causing intolerable situation for the crew on- board (**Case 2**). In the last stage, the excitation becomes severe such that the floating structure is anticipated to capsize leavingno choice for the crew rather than evacuating the structure urgently (**Case 3**). EWA will help to evaluate the performance of the structure for any desired level of storm conditions and any reasonable EDPs for future risk assessment and decision making processes.

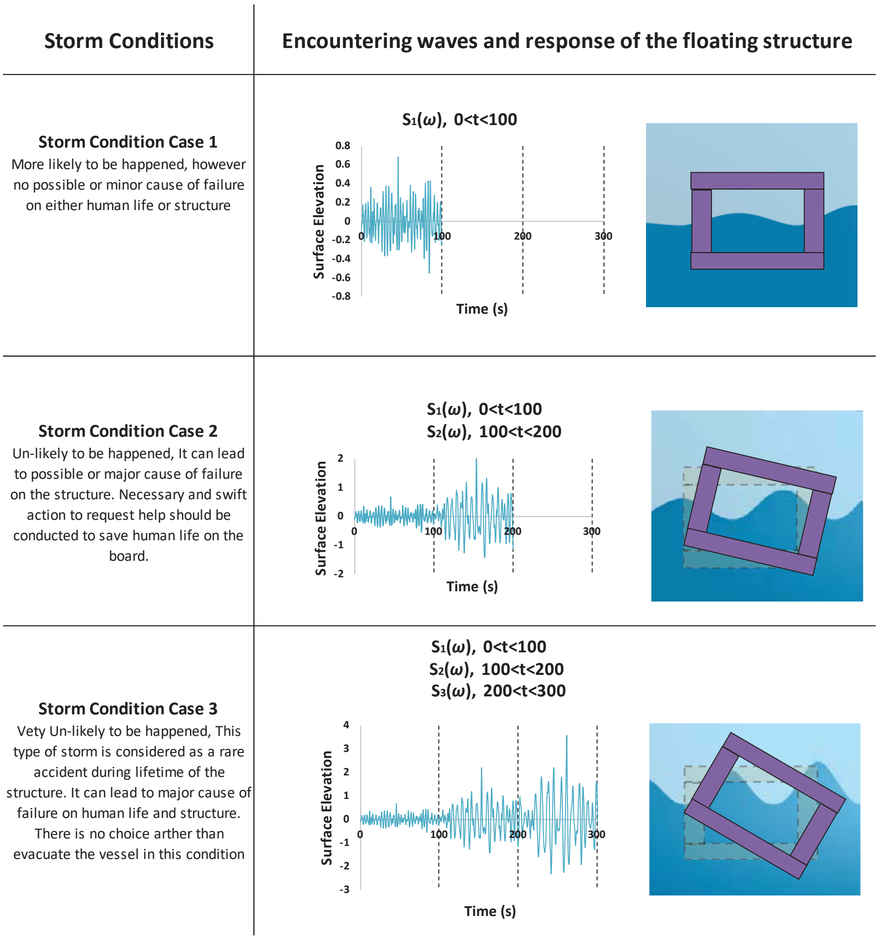


Figure 3.1 Adopted storm conditions based on the concept of EWA method

3.3 Intensifying Constrained New Wave Model (ICNWM)

CNW is a type of Gaussian process used to model random wave elevations constrained to the most probable new-wave crest at a specific time by considering sea spectrum. In addition to its shorter analysis time, CNW has the capability to model the random nature of the sea waves. The application of this method in determining the extreme response of the structures under wave loadings is proved by previous researches (Diznab et al. 2014; Jahanmard et al. 2015; Zeinoddini et al. 2012). Further details about CNW and its application is provided by Taylor et al. (1997).

To model of the three step storm condition, CNW is used for generating the Intensifying Wave Train Functions (IWTFs). For this purpose, using the sea spectrum, *m* separate time series of intensifying CNWs each with a specific sea state and constant duration time (t_d) are joined together to form a standalone time history of the random sea elevation. The k^{th} CNW profile, $\eta_{R_k}(t)$, represents the sea state k ($1 \le k \le m$) which is itself constructed based on the wave energy density spectrum $S_k(\omega)$ at a specific site. The k^{th} term of CNW profile consider a time period of $(k\ -\ 1)\times\ t_d < t < k \times t_d\ .\ S_k(\omega)$ By stepwisely increasing the level of wave spectrum with a linear trend, as k increases from 1 to k, the intensifying storm profile will be generated. The target operational and survival significant wave height, H_S, and its corresponding energy density spectrum $S(\omega)$ should be placed somewhere halfway and last stepwise profile through the sea states 1 to m. This assists in conducting risk escalation assessment since the performance of the structure can be evaluated when the storm condition exceeds the operational and survival limits of a marine floating structure. The first generation of ICNW in which the growth function is linear, can be expressed as follows (Diznab et al. 2014; Zeinoddini et al. 2012):

$$\eta_{ICNW}(t)=\begin{cases} \eta_{R_1}(t)+\rho_1(t)[\alpha_1-\eta_{R_1}(t_c)]+\dfrac{\dot{\rho}_1(t)}{\lambda_1^2}\dot{\eta}_{R_1}(t_c) & 0<t<t_d\ ,\ S_1(\omega) \\ \eta_{R_2}(t)+\rho_2(t)[\alpha_2-\eta_{R_2}(t_c)]+\dfrac{\dot{\rho}_2(t)}{\lambda_2^2}\dot{\eta}_{R_2}(t_c) & t_d<t<2\times t_d\ ,\ S_2(\omega) \\ \vdots & \\ \eta_{R_k}(t)+\rho_k(t)[\alpha_k-\eta_{R_k}(t_c)]+\dfrac{\dot{\rho}_k(t)}{\lambda_k^2}\dot{\eta}_{R_1}(t_c) & (k-1)\times t_d<t<k\times t_d\ ,\ S_k(\omega) \\ \vdots & \\ \eta_{R_n}(t)+\rho_n(t)[\alpha_n-\eta_{R_n}(t_c)]+\dfrac{\dot{\rho}_n(t)}{\lambda_n^2}\dot{\eta}_{R_1}(t_c) & (n-1)\times t_d<t<n\times t_d\ ,\ S_n(\omega) \end{cases} \tag{3.1}$$

where η_{ICNW} is the surface elevation of ICNW, k represents the k^{th} wave profile, t_c is the occurrence time of maximum expected wave, α_k is the crest elevation defined as

$\alpha_k = \beta H_{\max_k}$ .H_{Max_k} which is the most probable maximum wave height in the sea state k, can be expressed by $H_{\max_k} = 0.707 H_{S_k} \sqrt{\ln N_w}$ (Sorensen 2006). Where, N_W is the number of wave cycles during the storm period (t_d). The value of β, coefficient that refer to maximum wave height in each sea spectrum, when using JONSWAP spectrum, has been considered as $\beta = 0.58$ (Zeinoddini et al. 2012). Time dependent parameters $\rho_k(t)$ and $\dot{\rho}_k(t)$ are the unit new wave and its slope autocorrelation function, respectively. λ_k^2 is obtained from the second spectral moment and variance of the wave energy spectrum ($\lambda_k^2 = \frac{m_{2k}}{\sigma_k^2}$). $\eta_{R_k}(t)$ is a random process that can be written as:

$$\eta_{R_k}(t) = \sum_{n=1}^{N} c_{kn} \operatorname{Cos}(\omega_n t + \varepsilon_{kn}) \quad , \quad c_{kn} = \sqrt{2 S_k(\omega_n) \Delta\omega} \tag{3.2}$$

ε_{kn} is the random phase with a uniform distribution between $0-2\pi$, $S_k(\omega_n)$ is the wave spectrum value for ω_n in $S_k(\omega)$, _σ_k represents the standard deviation of $S_k(\omega)$ for the sea state *k*. By considering the characteristics of the sea waves on a specific site, the minimum required duration time, t_d, should be defined to develop the storm profile. In this study duration of 100 seconds is adopted to ensure a wave profile with all possible wave heights is developed during the storm.

3.4 Developed Methodology

The novel methodology developed in this study will contribute as a powerful tool for hydrodynamic analysis of marine structures during storm conditions to evaluate their critical performance. The outcome of the proposed methodology will assist the designer and vessel operators during harsh conditions to understand a better view of the structural behavior encountered storm. Therefore, the approach has the capability for future risk and reliability analysis for improving the safety of the marine operation. This methodology in general illustrated in Figure 3.2 and discussed in the following.

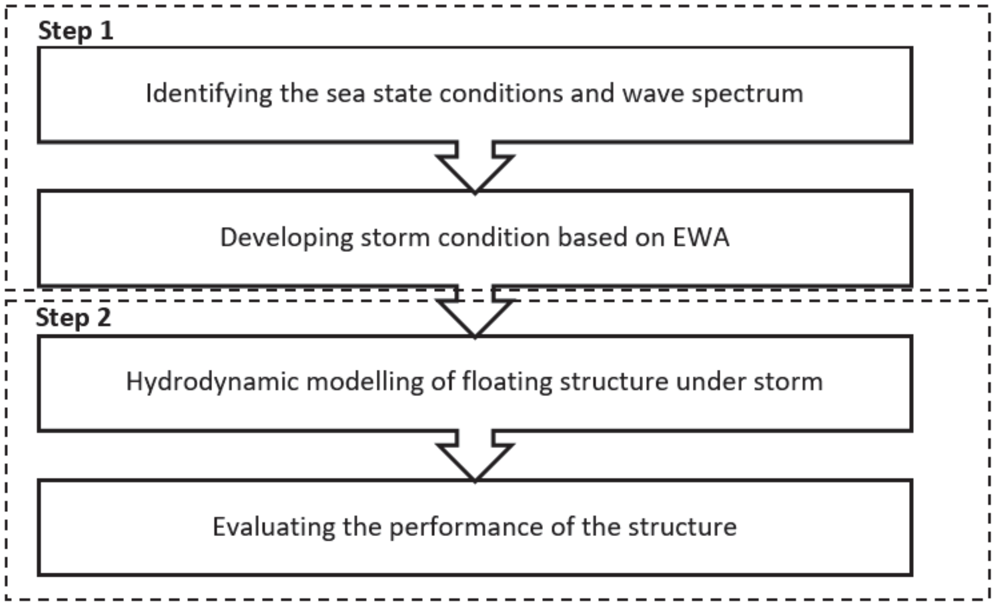


Figure 3.2 Sequence of the developed methodology for robust decision making that improves safety of humans on-board a floating structure under various storm conditions

To evaluate performance of marine floating structures in severe environmental conditions, it is necessary to analyze the stochastic dynamic behavior of the structure in various sea states. However, an extensive number of time-domain simulations is essential to evaluate extreme loads affecting the system. This study devotes to develop a novel methodology for hydrodynamic analysis of the floating structure under storm conditions. The approach is capable to generate the essential data for investigating the behavior of structure stochastically and it can use as the basis for future statistical analysis efficiently. For this purpose, EWA method is considered to develop ICNW function for two reasons: (1) to minimize the duration of the hydrodynamic time-domain simulation by representing a unique wave train function, (2) to reduce the extent of EDP data necessary for performance analysis of the structure. Therefore, the dynamic behavior of the system can be evaluated stochastically with only one simulation time which is more efficient computationally. In order to develop storm profile, firstly a number of different sea states according to their sea spectrum should be defined. Then EWA approach will apply to design intensifying wave train for harsh environment that representing storm situation. The fundamentals of EWA method is discussed in **section 3.2** clarifying all relevant hydrodynamic theories used in this paper. Figure 3.1 presents an overview of the hydrodynamic analysis for generating ICNW function based on EWA. Afterwards, the structure will encountered with storm for hydrodynamic modeling of a floating system. The final response results are then adopted for estimating the EDP for each storm condition to evaluate performance of the structure. The results will show that possible situation that the structure will exceed the survival condition during storm.

3.5 Application of the developed methodology: A case study

3.5.1 Scenario Development

To demonstrate the application of developed methodology, a case study is adopted for performance analysis of Sevan 1000 Floating Storage Unit (FSU) encountering storm. The structure is a storage unit incorporating a main cylindrical hull with diameter of 85 m and draft of 30 m. The area of the main deck is approximately 6790 m^2 and the symmetric radius of gyration in both roll and pitch are 28.2 m. This unit was intended to operate on the Mariner field in the United Kingdom sector of the North Sea (Hanssen 2013). Previously, a number of conventional studies were carried out to investigate the hydrodynamic characteristics of this unit focusing on its performance, however not in harsh environment and storm condition (Anundsen 2008; Hanssen 2013). In the present paper, Sevan Hull encountered to designed storm profile due to extreme environmental loads for evaluating the dynamic behavior of the structure in survival condition. According to Brindley and Comley (2014), a number of catastrophic failures are occurred on these structures operating in the North Sea due to its harsh environmental conditions. This highlights the need for developing a robust methodology that evaluate performance of the structure more realistically in storm conditions.

3.6 Developing ICNW Storm Profile (Step 1)

In order to develop the ICNW storm wave profile, eleven sea state thresholds are considered. The sea states used in implementing the ICNW profile respect to each sea state are presented in Table 3.1. To model the random and irregular nature of sea wave elevations JONSWAP spectrum is used for different sea state. Each sea states represent a spectrum, $S_k(\omega)$, for different k^{th} level of storm which is shown as sea states in Table 3.1. The considered survival limits for FSU operation based on the suggestions by Anundsen (2008) are defined as maximum wave height of 19 m, maximum roll angle of 9 degree, maximum surge and heave response of 12 m and 13 m respectively and maximum wind speed of 41 m/s. Using the ICNW profile and considering these operational safety limits, hydrodynamic analysis of the FSU conducted to evaluate the performance of the structure under different level of storm condition.

Table 3.1 The discretised Sea states used to model $S_k(\omega)$ that assist for generating ICNW for North Sea site

Sea State	Significant Wave Height, Hs (m)	Peak Spectrum Wave Period, Tp (s)
1	Hs <0.65	2.58
2	2.15	4.69
3	3.65	6.12
4	5.15	7.62
5	6.65	8.26
6	8.15	9.14
7	9.65	9.94
8	11.15	10.69
9	12.65	11.39
10	14.15	12.04
11	Hs >15.65	12.60

Moreover, to show the advantage of this method in reducing the simulation time, the superimposed conventional Random Sea Elevation (RSE) is compared with ICNW, as presented in Figure 3.3. As illustrated in the figure, the RSE profile needs more simulation time to observe extreme wave heights. It is usual to run numerical simulation of hydrodynamic analysis for 3-hours for each sea states to observe desired extreme wave heights as recommended by (Chen and Moan 2004; Ren et al. 2015; Veritas 2007). That is, for each sea state eleven 3-hours simulations are needed to be carried out in order to obtain a realistic representation of storm. However, to generate ICNW profile for this site, only 1100 seconds of simulation time is required to observe different level of extreme storm conditions in one individual simulation for hydrodynamic analysis. As an example, sea states five and eleven are illustrated individually in Figure 3.3 to emphasize differences between these two approaches and how the time domain in ICNW reaches its highest level in a much shorter time. In the figure, the wave spectrum for these sea states are shown above the surface elevation profile providing a qualitative representation of Eq. (3.1) and Eq. (3.2) described in section **3.1**.

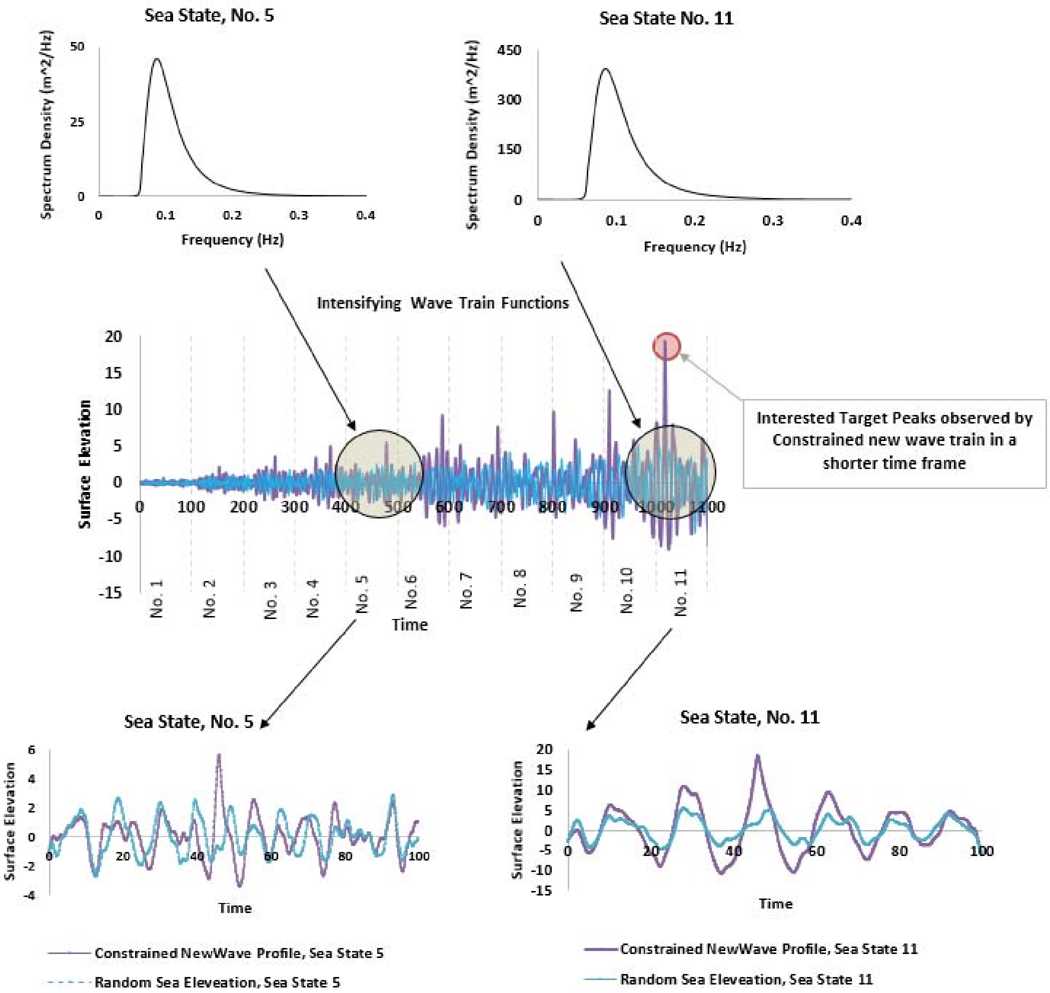


Figure 3.3 Developed ICNW storm profile based on eleven different sea state for the North Sea site.

3.7 Hydrodynamic Analysis (Step 2)

In this study *OrcaFlex* software is used to conduct the hydrodynamic analysis. ICNW wave profile is inputtted manually in the software to conduct the simulation process and time-domain analysis. The simulations are then carried out to investigate performance of the FSU. To explore the dynamic behaviour of the FSU in details, the most critical angle of attack considered as the performance analysis. By the conducted simulations in different angles, it is found that 45 degree has the most extrem response which adopted for the perfromance analysis.

To evalaute dynamic behaviure of FSU in extreme condition, the time history of Surge, Roll and Heave angle extracted from the results and represneted in Figure 3.4**.** Also, the relevant survival limit states are illustrated in each plot, to show the effect of intensifying level of storm in each sea state on the performance of the structure. It is found that, when the storm reach to the significant wave height of 12.56 meter, which is 9th level in the designed wave profile, then the heave and surge motion exceed the survival condition limit. This limit for roll degree will surpass in 10th level in significant wave height of 14.15 meter. In general the vessel can survive for a wide range of incident waves lower than 9th level to being in safe zone. These criteria are essential for future risk and reliability analysis of the marine floating structure during their operation to minimize any possible structural failure, such as capsizing the vessel due to harsh conditions. It is also essential to investigate the coupled motions of the structure during storm to define the situations that exceed the survival limit. For this purpose, trajectory plot of transition and rotational motion are considered to illustrate the stochastic dynamic behaviour of the vessel. Figure 3.5 represents the trajectory motions of Roll/Pitch and Surge/Sway degrees respectively. The results demonstrate the critical borders that the vessel will experience extreme response that can result in capsizing or major damage on the structure due to impact of sea loads. Moreover the graph shows the frequency of the cases that vessel exceed its safe limit, e.g. during the storm condition in the simulation time of 1100 second, the vessel pass the safe border three times for pitch angle and nine times for sway direction which is imperative values for future risk and reliability analysis to find the chance that the structure remain in unsafe zone. The survival conditions are shown in the plots to clarify structure exceed the critical limits. These graphs are important for future failure analysis of the structure as it shows the number of occurrence that the structure exceed the survival condition. By intensifying the storm level, the discrepancy of the coupled responses will increase drastically. This means that the structure will experience extreme responses that will affect the marine operation. The border that is highlighted in both figures show the safe region during the storm. The coupled response of Surge/Sway is more likely to exceed the survival limit condition while the dispersion of the Roll/Pitch motion increase by intensifying the storm. All these stochastic behaviours will cause intolerable operation situation due to large motions either for structure or human life. These response should be considered to improve the safety of the operation and to examine the safety of the structural performance in different levels of the storm.

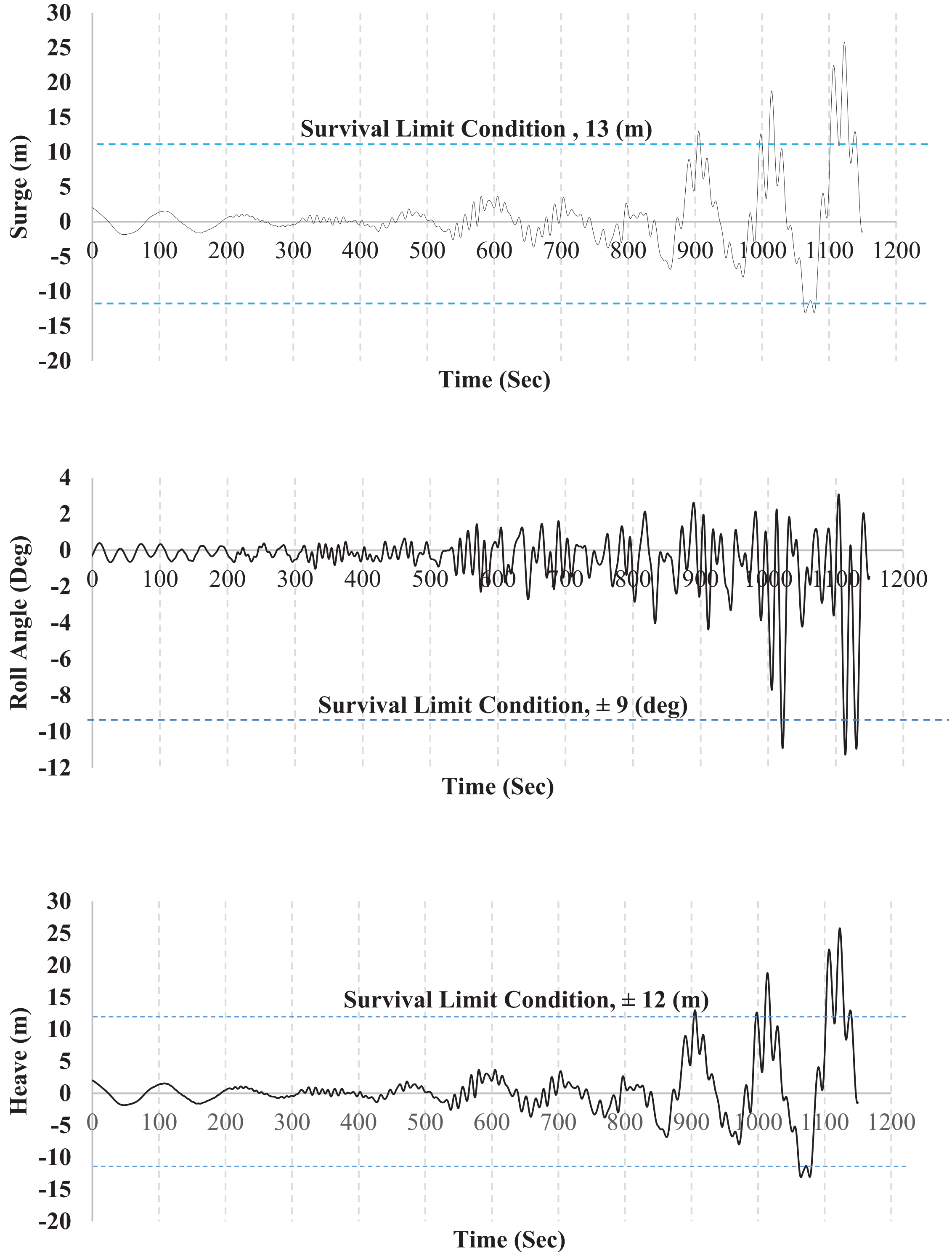


Figure 3.4 Time history of Surge, Roll and Heave angle under storm condition.

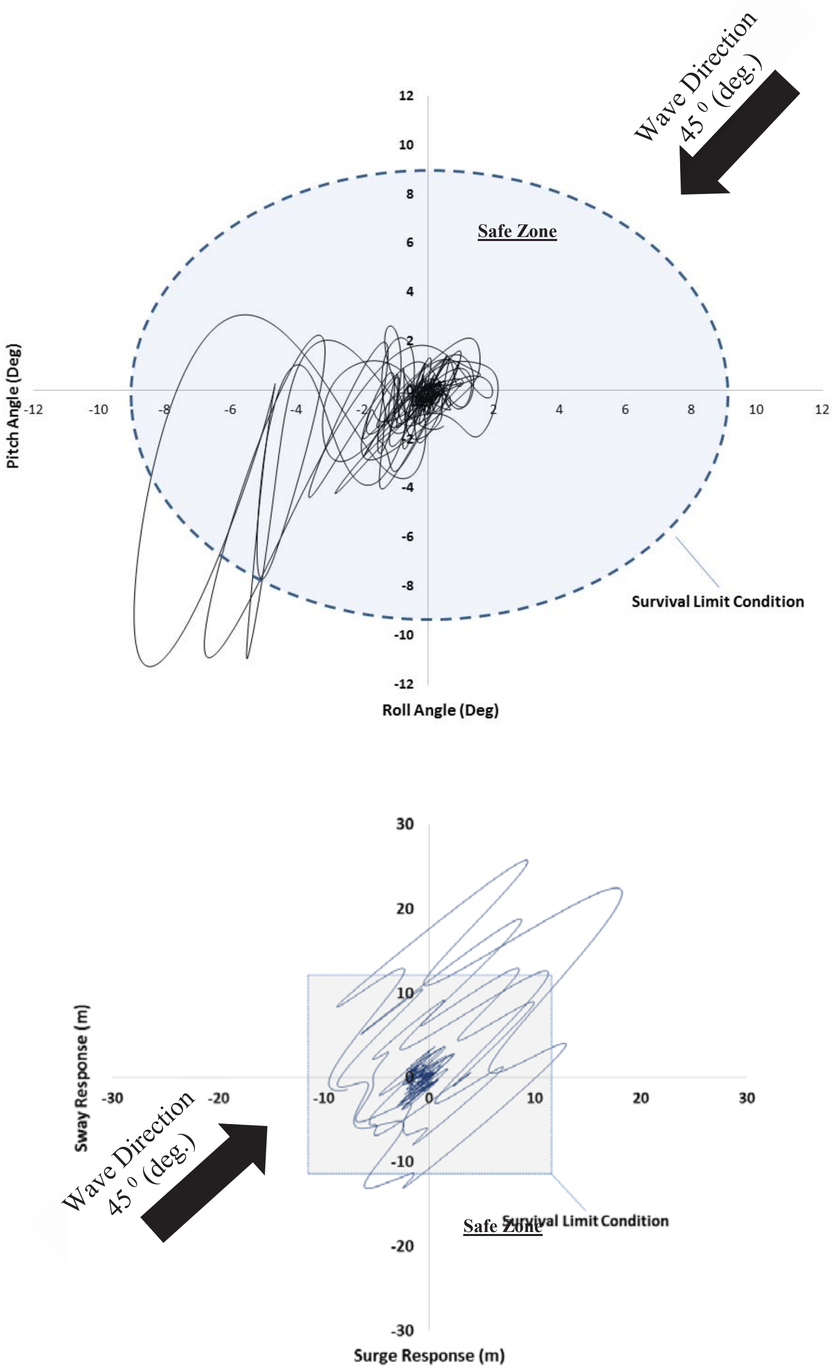


Figure 3.5 Trajectories of the Sway and Surge motions during storm

3.8 Conclusion

A new approach for hydrodynamic analysis of marine floating structure developed in this paper with the aim at elaborating performance of the object during storm. The methodology starts with designing a user-defined storm profile by superimposing through intensifying wave train function in different sea states. This approach has the advantage of evaluating hydrodynamic response of the structure encounter with storm in a single time history with the fact that reducing computation cost of simulations. The advantages of the proposed framework were demonstrated through simulating a FSU in storm condition. The results of the analysis indicate that the structure will exceed the survival condition if the storm pass the significant wave height level of 12.65 meter. In addition, the global trajectory of the vessel for transition and rotational response demonstrates the effect of storm on the performance of the structure. The results of this study highlight that the proposed methodology can be used as a useful framework for future risk and reliability analysis considering the dynamic behavior of a floating structure to minimize the possible failures such as capsizing. This analysis enables the designers and operators to assess the reliability of the structures encountering extreme sea state conditions.

4. A Robust Risk Assessment Methodology for Safety Analysis of Marine Structures under Storm Conditions

Abstract

Accidents involving vessels and/or offshore structures (henceforth referred to as marine structures) may pose high financial, environmental and fatality risk. To effectively manage these risks a methodical approach is required to model accident load and the stochastic behaviour of the marine structure that are arising from storm effects. This paper introduces a proactive framework that identifies and considers all the initial relevant risks. Compared to the conventional approaches that rely on precursor data for accident modelling, the developed methodology utilizes the critical stochastic variables directly from the hydrodynamic analysis of the floating structure. For this purpose, a novel numerical model is proposed to replicate a storm based on Endurance Wave Analysis (EWA) method. This approach reduces the computational cost (time and load) of the simulations. The critical stochastic variables are subsequently used in Bayesian Network (BN) to develop the risk model. The EWA and BN based integrated methodology assists in better understanding of accident causation and associated risk in changing operational conditions. The application of the methodology is demonstrated through a Floating Storage Unit (FSU) experiencing capsizing scenario.

Keywords: Bayesian Network, Decision Making, Influence Diagram, Storm, Endurance wave analysis, Reliability

4.1 Introduction

Failure in operations conducted in the marine environment may pose various major risks in terms of environmental pollution and loss of assets for companies. In the majority of cases, such as exploration of oil and gas reserves and marine transportation, this industry also engages with human life, where accidents may cause human casualties. Therefore, a great deal of research on the improvement of marine safety is carried out to mitigate the associated risks. It is also necessary to take into account the process of risk escalation in a more realistic way rather than relying only on either precursor data or expert judgments. This requires a comprehensive approach when it comes to accident modelling and risk analysis of marine floating systems. However, due to irregularities in the sea environment, the nonlinear dynamics of floating system should be taken into consideration when developing a reliable measure of safety. Catastrophic hurricanes such as Ivan, Katrina and Rita in the Gulf of Mexico highlighted the importance of considering the impact from extreme environmental loads on all types of offshore structures. A large number of marine accidents, such as extreme responses of vessels encountering rough sea waves, have occurred due to harsh environment. For instance, the Mediterranean Sea migrant shipwreck and the Demas Victory a Dubai-based supply ship that sank off the coast in rough seas (Townsend 2015). These accidents resulted in at least 150 casualities reflecting the detrimental consequences of such disasters on human life. Review of recent maritime disasters confirms that there is a lack of a framework that enables making the optimum decision in case floating structures are about to capsize (Montewka et al. 2014). The critical question is how the safety of the crew on-board can be improved during a marine accident, and how they should manage the situation to survive. That is, if the operating crew were to be supported with a risk-assessment tool that uses the responses of the vessel in different conditions for predicting survivability, they would be able to decide whether to ask for rescue or immediately evacuate the vessel before the accident occurs.

Most of the existing risk assessment models are based on historical data obtained from previous marine accidents, and thus they can be considered reactive instead of proactive (Montewka et al. 2014). For example, Papanikolaou and Eliopoulou (2008) and Konovessis and Vassalos (2008) conducted a risk evaluation study based on regulations and worldwide accident experiences, from 1994 to 2004, respectively, to maximize marine transportation safety. With the similar objective, a number of studies have been conducted by previous researchers for improving the level of safety in floating structures (Guarin et al. 2009; Mermiris et al. 2008; Papanikolaou et al. 2010; Papanikolaou et al. 2012; Trucco et al. 2008). Recently, Montewka et al. (2014) introduced a systematic framework to estimate the risk for maritime transportation systems with regard to risk escalation based on proactive approaches. However, their method did not consider the associated risks that arose due to harsh environment such as extreme wave loads. There is also no robust tool available to investigate the effect of floating systems responses on human actions on-boards during storm conditions. This motivation will then be reason to investigate the causality of possible accident scenarios in marine harsh environment by the means of advanced probabilistic model. For this purpose, it is essential to integrate the recent approaches of nonlinear dynamic analysis of floating structures with advanced probabilistic models to develop a strong risk assessment tool for improving the safety of marine operations in a harsh environment.

For the sake of risk aseessment and decision making, application of several methods were found in the literature among which Maximum Likelihood Estimation (MLE) and Bayesian statistics are recommended for reliability analysis (Sørensen 2004). To perform a risk-based decision making , Bayesian Network (BN) are increasingly used due to their advantages over other methods such as Fault Tree Analysis (FTA) as discussed by Khakzad et al. (2011), Friis-Hansen (2000), Straub (2004), Tavner et al. (2007). There are three main reasons that Bayesian approaches have been adopted by previous researches. Firstly, this probabilistic model is a promising tool in risk and reliability engineering that allows the comprehensive reflection of available knowledge about the process (Abaei et al. 2018a, Abaei et al. 2018b, Abaei et al. 2018c; Arzaghi et al. 2017, Abaei et al. 2017; Groth et al. 2010; Khakzad et al. 2011; Montewka et al. 2014; Musharraf et al. 2014; Trucco et al. 2008). Secondly, in comparison to other tools such as Analytic Hierarchy Process (AHP), BN performs better in solving decision-making problems when extended to an Influence Diagram (Daniel 2009; Friis-Hansen 2000). Thirdly, in a Bayesian approach, it is also possible to convert continuous random variables into a discrete space, enabling the inference of more complicated stochastic relationships amongst many parameters (Friis-Hansen 2000). That is, each variable involved in the problem can be analyzed explicitly rather than in a binary space (true or false).

To develop a risk assessment and decision-making framework, an optimum method is required for generating the data that represents the stochastic behavior of the structure in storm condition. Conventional dynamic analysis of marine structure is a time consuming approach as it needs a longer simulation time to generate data for conducting statistical analysis (Agarwal and Manuel 2009). As an example, Haibo Chen and Moan (2004) carried out a study with twenty different three-hour time-domain simulations to extract the time series of the structure responses. It is therefore necessary to rely on a method that reduces the simulation time for more efficent analysis. Recently, Endurance Time Analysis (ETA) method was developed by Riahi et al. (2009) and later improved by Riahi and Estekanchi (2010) to reduce the computational cost of simulation times. Engineering Demand Parameters (EDPs) such as stress in structural members were investigated through the time-domain records (Zeinoddini et al. 2012). Results of the studies carried out by Estekanchi et al. (2007); Estekanchi et al. (2011) and Riahi and Estekanchi (2010) demonstrate the efficiency and accuracy of this method over conventional methods in the dynamic evaluation of structures during natural disasters such as earthquakes.

Therefore, considering BN as a probabilistic model and ETA as an efficient tool for dynamic analysis of the structure, an integration of theses method should be provided for effective risk assessment. Based on this, this paper aims at developing a robust methodology to improve safety during marine operations. The study will focus on developing a hydrodynamic model to simulate a real condition of the vessel while encountering a storm. Therefore, other events such as loss of communication or loss of engine are not considered in the proposed framework.Since the dynamic behaviour of the structure is the key point of a marine accident, this methodology utilizes the stochastic nature of the critical response variables of a floating unit. The critical response variables are integrated in the BN to model the structure's failure. The developed BN is then extended to an Influence Diagram (ID) for risk assessment purposes. To illustrate the effectiveness of the methodology, a Floating Storage Unit (FSU) is considered.

The remainder of this paper is divided into the following sections; Section 4.2 explains the concept of critical response variables in evolving operational conditions. Section .43 an introduction to BN and ID is presented. Section .44 discusses the developed methodology and its elements. Section 4.5 demonstrates the application of the methodology in a real case study and Section 4.6 concludes the paper providing the main findings and recommendations for possible future studies.

4.2 Response of the critical variables using endurance wave analysis

EWA is a simulation-based approach that evaluates the hydrodynamic performance of offshore structures when encountering a wave profile with stepwise increases in the wave height. In EWA method, different sea states are provided in a single time domain by introducing an Intensifying Constraint New Wave (ICNW) function. Accordingly, this approach can be adopted for simulating the increasing trend of storms levels over time, which go well beyond the design sea state accounting for the random nature of sea waves.

Figure 4.1 illustrates the three different levels of ICNW profile with different sea states that are adopted for the hydrodynamic simulations of the floating structure. At the beginning, the structure is subjected to a time history of a wave load corresponding to a certain significant wave height (H_s) and peak spectral period (T_p) derived from the first and lowest level of sea state associated with its sea spectrum ($S_1(w)$). Since the amplitude of the excitation is quite low, the structure remains stable while experiencing this loading (**Case 1**). In the second stage, the significant wave height is increased linearly for the same time duration as case 1. At some point during this stage of storm, the structure will exceed its survival limit causing an intolerable situation for the crew on- board (**Case 2**). In the last stage, the excitation becomes severe such that the floating structure is anticipated to capsize (**Case 3**). EWA will help to evaluate the performance of the structure for any desired level of storm conditions and useful reasonable EDPs for future risk assessment and decision making processes.

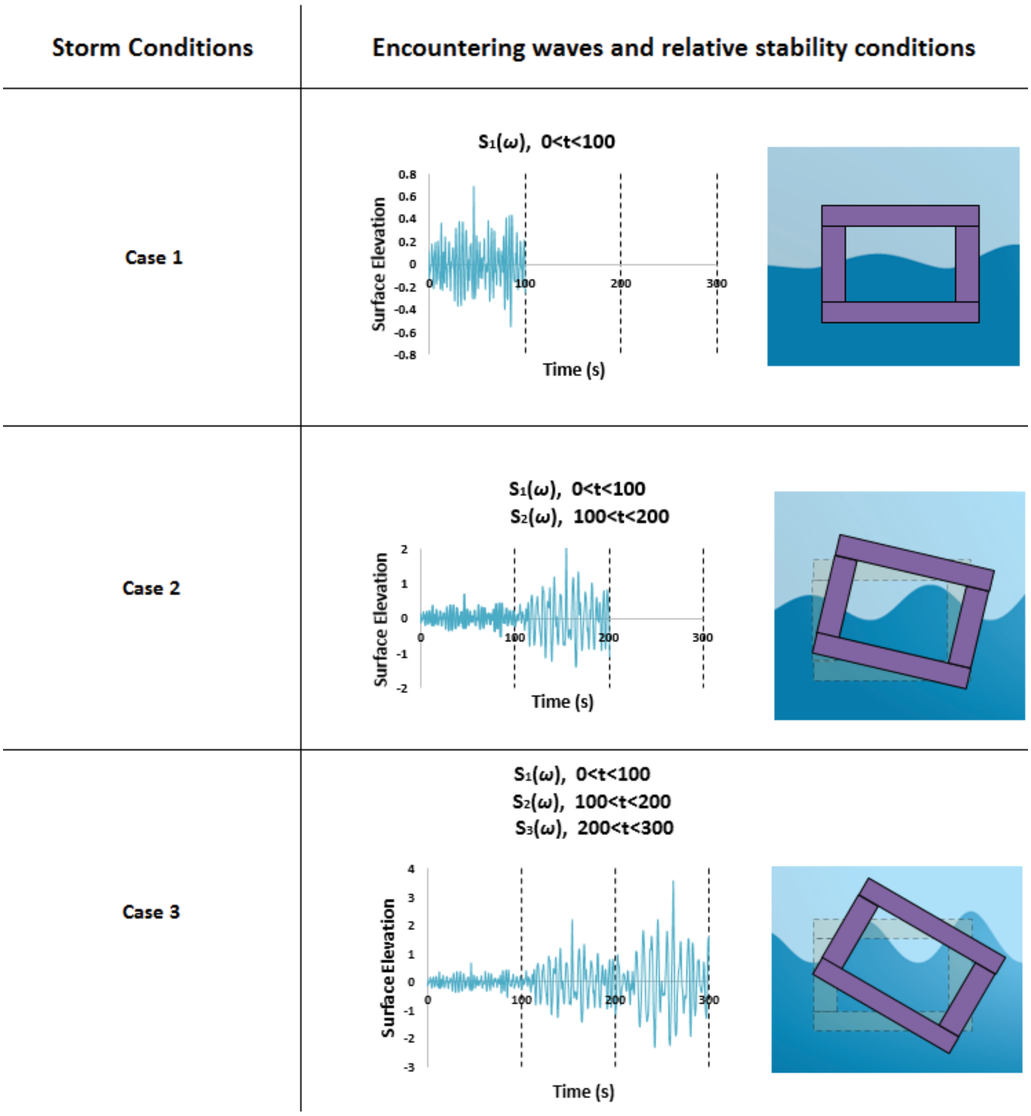


Figure 4.1 Adopted storm conditions based on Endurance Wave Analysis method

4.3 Intensifying Constrained New Wave Model (ICNWM)

To model the time history of a storm, different sea spectra with m separate time series of stepwise ICNW functions will be considered with constant duration time (t_d). The k^{th} step profile, $\eta_{R_k}(t)$, represents the sea state k ($1 \le k \le m$) which is itself constructed based on the wave energy density spectrum $S_k(\omega)$ at a specific site. The k^{th} step covers a time period of $(k-1)\times t_d < t < k \times t_d$. By increasing stepwise the level of wave spectrum through different steps with a linear trend, as k increases from 1 to n, the intensifying storm profile will be generated. The first generation of ICNW in which the growth function is linear, can be expressed as follows (Diznab et al. 2014; Zeinoddini et al. 2012):

$$\eta_{ICNW}(t) = \begin{cases} \eta_{R_1}(t) + \rho_1(t)[\alpha_1 - \eta_{R_1}(t)] + \dfrac{\dot{\rho}_1(t)}{\lambda_1^2}\dot{\eta}_{R_1}(t) & 0 < t < t_d ,\ S_1(\omega) \\ \eta_{R_2}(t) + \rho_2(t)[\alpha_2 - \eta_{R_2}(t)] + \dfrac{\dot{\rho}_2(t)}{\lambda_2^2}\dot{\eta}_{R_2}(t) & t_d < t < 2\times t_d ,\ S_2(\omega) \\ \vdots & \\ \eta_{R_k}(t) + \rho_k(t)[\alpha_k - \eta_{R_k}(t)] + \dfrac{\dot{\rho}_k(t)}{\lambda_k^2}\dot{\eta}_{R_1}(t) & (k-1)\times t_d < t < k\times t_d ,\ S_k(\omega) \\ \vdots & \\ \eta_{R_n}(t) + \rho_n(t)[\alpha_n - \eta_{R_n}(t)] + \dfrac{\dot{\rho}_n(t)}{\lambda_n^2}\dot{\eta}_{R_1}(t) & (n-1)\times t_d < t < n\times t_d ,\ S_n(\omega) \end{cases} \tag{4.1}$$

where η_{ICNW} is the surface elevation of ICNW, $\eta_{R_i}(t)$ is the wave profile representing ith storm level, t_d is the constant period of time that storm will generate to observe extreme wave heights, k represents the k^{th} wave profile, α_k is the crest elevation defined as $\alpha_k = \beta H_{\max_k}$. H_{Max_k} which is the most probable maximum wave height in the sea state k, can be expressed by $H_{\max_k} = 0.707 H_{S_k}\sqrt{\ln N_w}$, (Sorensen 2006). Where, N_W is the number of wave cycles during the storm period (t_d). The value of β coefficient that refers to maximum wave height in each sea spectrum, when using JONSWAP spectrum, has been considered as $\beta = 0.58$ (Zeinoddini et al. 2012). Time dependent parameters $\rho_k(t)$ and $\dot{\rho}_k(t)$ are the unit new wave and its slope autocorrelation function respectively. λ_k^2 is obtained from the second spectral moment and variance of the wave energy spectrum ($\lambda_k^2 = \dfrac{m_{2k}}{\sigma_k^2}$). $\eta_{R_k}(t)$ is an irregular sea wave for each wave profile. By considering the characteristics of the sea waves at a specific site, the minimum required duration time of each storm level, t_d, should be defined to develop the storm profile. In this study a duration of 100 seconds is adopted to ensure a wave profile with all possible wave heights is developed during the storm.

4.4 Application of Bayesian network in accident modeling

BN is a graphical model for reasoning under uncertainty that uses causal relationships (represented by directed edges) among components of a system (represented by chance nodes). BN estimates the joint probability distribution of a set of random variables based on the conditional independencies and the chain rule, as stated in Eq. (4.2). An extensive review of BN and probabilistic knowledge elicitation including its applications in risk and reliability analysis is provided by Barber (2012), Scutari (2014) and Benson (2015).

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(X_i \mid pa(X_i)) \tag{4.2}$$

where $pa(X_i)$ is the parent set of variable X_i. As an example, the joint probability distribution of the random variables X_1 - X_4 shown in Figure 4.2 is estimated by $P(X_1, X_2, X_3, X_4) = P(X_1)P(X_2)P(X_3 \mid X_1, X_2)P(X_4 \mid X_3, X_2)$:

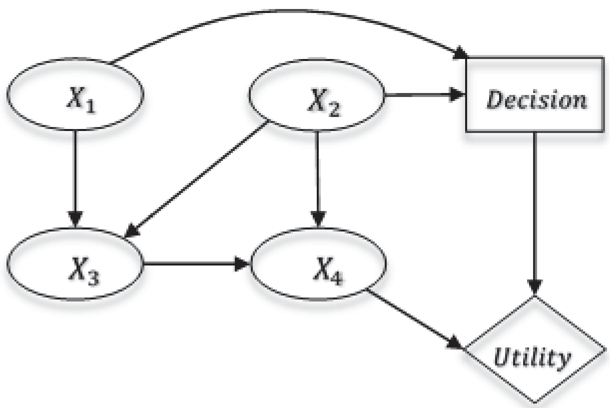


Figure 4.2 A schematic Bayesian network and an influence diagram (Decision and Utility nodes are added to BN)

In case new information becomes available for one or more chance nodes, BN is able to update the joint probability based on the Bayes' theorem:

$$\boldsymbol{P(X \mid E)} = \frac{\boldsymbol{P(X, E)}}{\sum_X \boldsymbol{P(X, E)}} \tag{4.3}$$

Friis-Hansen (2000) provides a more detailed explanation of BN concepts and its inference algorithms. The application of BN in the field of risk and reliability is explored by many researchers. A few recent examples include Abbassi et al., 2016; Bhandari et al., 2016; Yeo et al., 2016.

As an extension to BN, an influence diagram (ID) is proposed for the ease of probabilistic decision-making. The ID connects decision and utility nodes to the network (see Figure 4.2).

Decision nodes hold a number of decision alternatives considered by the user. The parents of a decision node provide the information required for making the decision node. Therefore, the edge pointing to a decision node is an information arc instead of a probabilistic dependence (Friis-Hansen, 2000). Consisting of numeric values rather than probabilities, utility nodes demonstrate the decision maker's preference over each configuration of a decision alternative. For instance, if there exist n states for node X_4 and m alternatives for the decision node, the utility table requires $n \times m$ numeric values. The expected utility of decision alternative d_i is then estimated using Eq. (4.4). The alternative with maximum expected utility will be the optimum decision.

$$\boldsymbol{EU(d_i)} = \sum_{X_4} \boldsymbol{P(X_4 \mid d_i)\, U(d_i, X_4)} \tag{4.4}$$

These utility values are determined based on experts' knowledge or utility functions. Jensen and Nielsen (2007) provide extensive information about influence diagrams. To name a few, Nielsen and Sørensen (2010) used ID to develop a decision making tool for optimizing the operation and maintenance costs of offshore wind turbines. Eleye-Datubo et al. (2006) illustrated the applicability of BN and ID in decision making problems through a marine vessel evacuation in an accident and a collision scenario of an offshore structure. They asserted that ID could assist in integration of a large number of interacting issues and their effects on the decision. They also reported that by providing practical solutions for optimization tasks, IDs can be used as robust marine decision-support tools.

4.5 The proposed methodology

The methodology proposed here is a robust risk assessment tool with the aim of improving safety during the operation of a marine floating structure. This tool will assist the operators in taking the optimum action with respect to the survival condition of the structure while encountering evolving conditions such as storm. The outcome of the proposed methodology will assist the vessel operators to mitigate the risk of loss of human life. This methodology consists of three different steps as presented in Figure 4.3. These steps are discussed in the following sections.

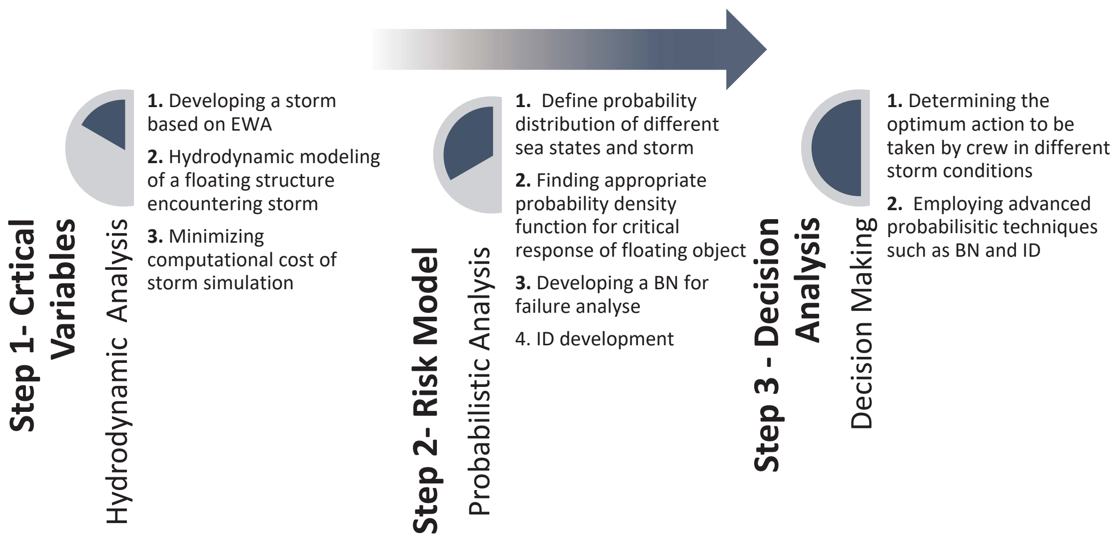


Figure 4.3 The sequence of the developed methodology

4.5.1 Hydrodynamic Modelling (Step 1)

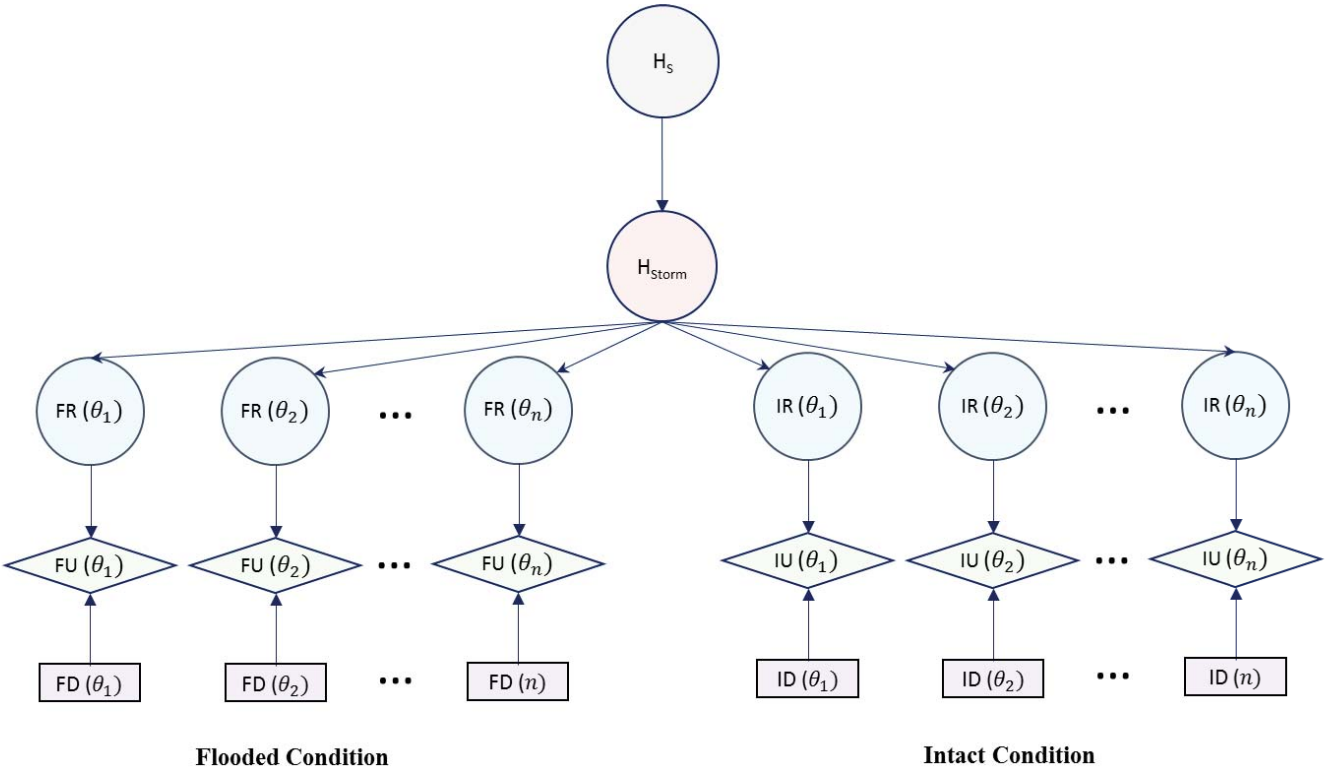
To conduct a comprehensive risk and reliability assessment of marine floating structures in severe environmental conditions, it is necessary to analyze the stochastic behavior of the structure in various sea states. In this way, for statistical extrapolation, a large number of time-domain simulations is essential to evaluate extreme loads affecting the system. The first phase of this methodology focuses on hydrodynamic modelling of the floating structure subjected to a storm. This will generate essential data for investigating the performance of structure stochastically and will be used as the basis for developing the risk assessment tool. For this purpose, EWA method is employed for developing ICNW function for two reasons: (1) to minimize the duration of the hydrodynamic time-domain simulation by presenting a unique wave train function and (2) to reduce the extent of EDP data necessary for risk assessment and future decision making. Therefore, the dynamic behavior of the system can be evaluated stochastically with only one simulation time, which is computationally more efficient. The results of this step are then adopted for estimating the EDP for each storm level and further used as the input for the second and third part of the methodology. The fundamentals of EWA method are discussed in Section 2 clarifying the hydrodynamic theories used in this paper.

4.5.2 Risk Model and Decision-Analysis (Steps 2 and 3)

The second and third step of the study is devoted to the risk model development, and conducting probabilistic analysis of the EDPs and long term prediction of storm conditions. The simulation data obtained during the hydrodynamic analysis will be employed to estimate the probability of failure a floating structure. A statistical analysis is performed to define a suitable probability density function for each EDP. Maximum Likelihood Estimation (MLE) method is then applied to estimate the distribution parameters such as shape and scale factor for each case. To investigate the effect of different levels of storm on EDPs, a probabilistic network is developed using BN approach. In this study, to conduct the probability analysis using BN, GeNIe software is employed. In order to improve the safety of crew on a floating structure that may experience extreme environmental loads, it is necessary to consider the most critical scenarios in which the structure may have intolerable conditions for humans to stay on-board or it may even capsize. Moreover, it is crucial to evaluate the safety structure both in intact and flooded condition for various angles of incident wave, analyzing the effect of EDP variations on the decision-making process. In order to reflect these concerns, this methodology aims to determine: 1) which level of storm is the most critical condition during the operation? 2) What is the optimum decision alternative that should be taken by the operators during the storm condition? For this purpose, three alternatives are assigned for decision-making including a) Halting the operation and staying on-board; b) requesting help from a rescue helicopter or a vessel; c) evacuating the floating structure urgently. The BN will be able to evaluate extreme response of the structure encountering the storm from different angles of attack in both intact and flooded condition.

The developed BN enhanced for decision making process is represented in Figure 4.4. Node Hs represents the long-term probability of each sea state corresponding to i^{th} sea spectrum $S_i(\omega)$ while node H_{storm} incorporates the probability of different levels of storm defined by

ICNW profile. Nodes FR_1, FR_2, ..., FR_n and IR_1, IR_2, …, IR_n represent the probability of EDPs exceeding their critical limits (survival and capsizing criteria). Nodes FD_1, FD_2, …, FD_n and ID_1, ID_2, …, ID_n incorporate the different decision alternatives that operators may take for mitigating the risk of fatality. Nodes FU_1, FU_2, …, FU_n and IU_1, IU_2, …, IU_n include the assigned utilities based on the preference of operators over the decision alternatives and possible responses of the structure.



H_s	Long-term probability distribution of significant wave height
H_{Storm}	Probability of different level of storm condition encountered by ICNW profile
FR/IR (θ_n)	Flooded/Intact Response in n^{th} Degree
FU/IU (θ_n)	Flooded/Intact Utility in n^{th} Degree
FD/ID (θ_n)	Flooded/Intact Decision in n^{th} Degree

Figure 4.4 Developed Influence Diagram for risk-based decision making under various sea conditions

4.6 Case Study: A Floating Storage Unit (FSU) in the North Sea under Storm

4.6.1 Scenario Development

To demonstrate the application of developed methodology, a case study is adopted for evacuation of Sevan 1000 Floating Storage Unit (FSU) encountering a storm. This structure is designed to operate in the Mariner field in the North Sea (Hanssen 2013). The structure is a storage unit incorporating a main cylindrical hull with diameter of 85 m and draft of 30 m. The area of the main deck is approximately 6790 m^2 and the symmetric radius of gyration in both roll and pitch are 28.2 m. Previously, the hydrodynamic characteristic of this unit has been investigated through conventional methods focusing on its performance in operational and survival condition (Anundsen 2008; Hanssen 2013). In the present paper, however, Sevan Hull is selected for risk assessment and modelling failure due to extreme environmental loads. In this study, the structure will be subjected to a simulated storm causing it to become susceptible to capsizing. The method will identify the most efficient action that the operators may take for saving the crew's safely.

4.6.2 Developing ICNW Storm Profile

In order to develop the ICNW storm wave profile, eleven sea state thresholds are considered each of which has a specific long-term probability of occurrence. A three-parameter Weibull distribution is adopted for the selected North Sea site to model the long-term probability of significant wave heights as recommended by Karadeniz et al. (1983), Siddiqui and Ahmad (2000), and Karimirad and Moan (2013). The sea states used in implementing the ICNW profile as well as the discretized probabilities of each sea state are presented in Table 4.1. The operational and survival limits for FSU operation based on the suggestions by Anundsen (2008) are summarized in Table 4.2. The term "operation" here is an indication of the voyaging (i.e. general motion) of the vessel. By using the ICNW profile and considering these operational safety limits, risk escalation processes will be employed to evaluate the performance of the structure under different levels of storm.

Table 4.1 Discretized sea states probabilities used to generate ICNW for North Sea site

Sea State	Significant Wave Height, Hs (m)	Peak Spectrum Wave Period, Tp (s)	Long-Term Probability of Occurrence, $Pr(Hs)$
1	Hs <0.65	2.58	2.09E-01
2	2.15	4.69	4.35E-01
3	3.65	6.12	2.28E-01
4	5.15	7.62	8.85E-02
5	6.65	8.26	2.82E-02
6	8.15	9.14	7.74E-03
7	9.65	9.94	1.87E-03
8	11.15	10.69	4.06E-04
9	12.65	11.39	7.98E-05
10	14.15	12.04	1.44E-05
11	Hs >15.65	12.60	2.75E-06

Table 4.2 Operation safety limits for offshore floating storage units (Hanssen 2013)

Condition	Wind Speed (m/s)	Significant Wave Height, Hs (m)	Pitch/Roll Angle
Operational Conditions	32	8.5	4.0
Survival Condition	41	19	9

To model the random and irregular nature of sea wave elevations, JONSWAP spectrum is used. Moreover, to show the advantage of this method in reducing the simulation time, the superimposed conventional Random Sea Elevation (RSE) is compared with ICNW, as presented in Figure 4.5. As illustrated in Figure 4.5, the RSE profile needs more simulation time to observe the extreme wave heights. It is usual to conduct 3-hour simulations for each sea state to observe desired extreme wave heights as recommended by (Haibo Chen and Moan 2004; Ren et al. 2015; Veritas 2007). That is, for each sea state eleven 3-hour simulations are needed to obtain a realistic representation of storm. However, to generate ICNW profile for this site, only 1100 seconds of simulation time is required to capture an extreme storm condition in one individual simulation. As an example, sea states five and eleven are illustrated individually in Figure 4.5 to emphasize the sharp differences between these two approaches and how the time domain in ICNW reaches its highest level in a much shorter time. In the figure, the corresponding wave spectra for these sea states are shown above the surface elevation profile providing a qualitative representation of Eq. (4.1) described in **Section 4.2**.

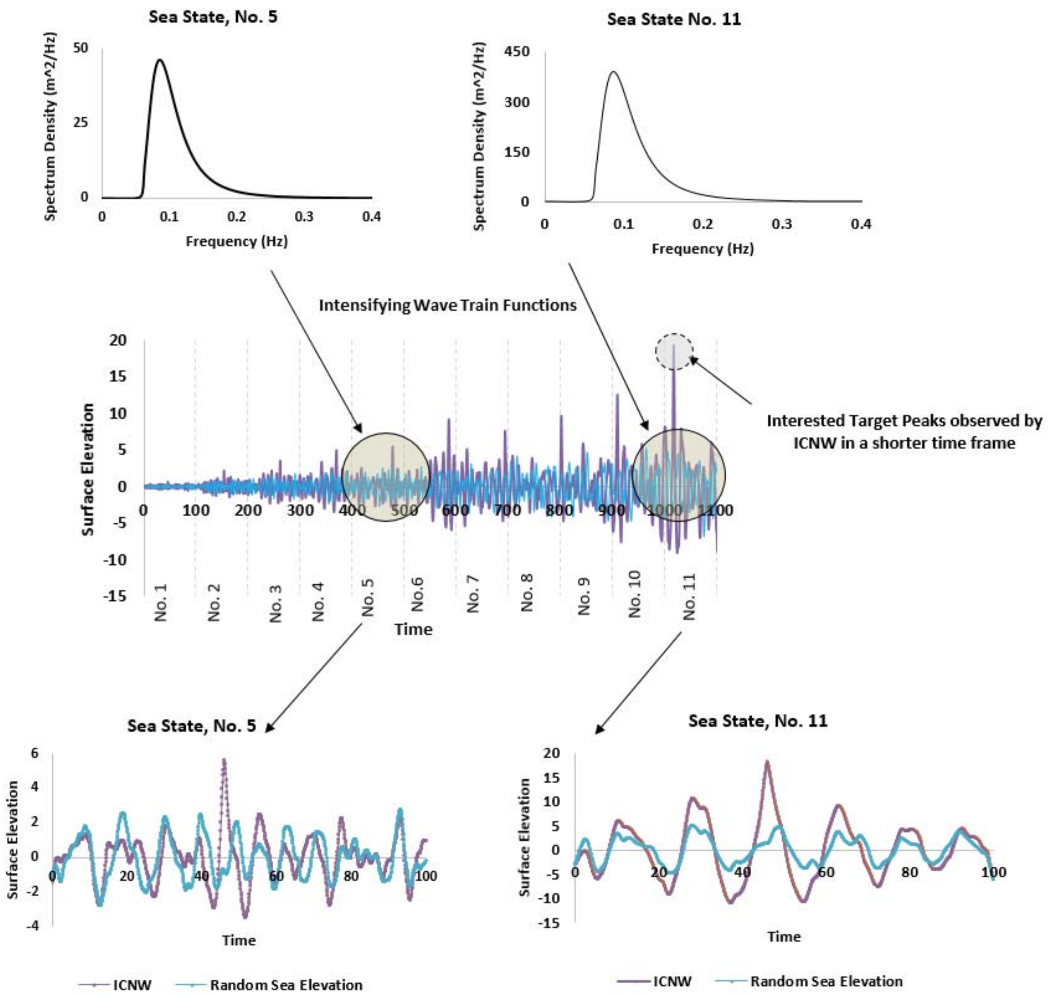
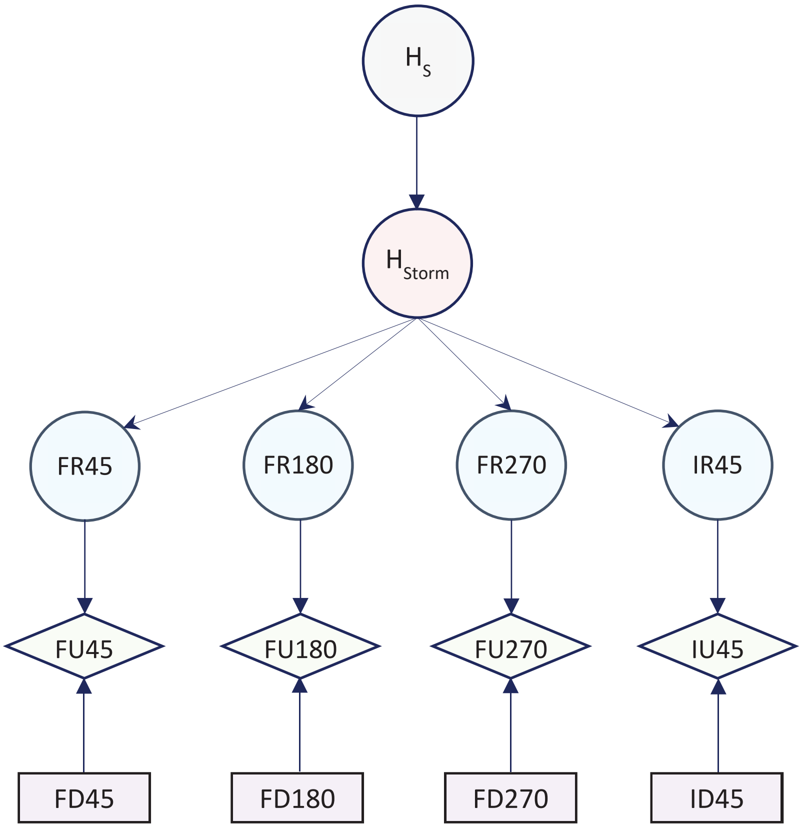


Figure 4.5 Developed ICNW storm profile based on eleven sea states for the North Sea site

4.6.3 Hydrodynamic Analysis

Two different scenarios are considered to evaluate the hydrodynamic characteristics of the floating structure in the extreme environment. First scenario is the *Intact Condition* where the floating object is in its upright condition and encounters ICNW from different angles of incidents. Second scenario is the *Flooded Condition* in which a constant heel angle is applied to the structure due to a damaged compartment. The simulations are then carried out to investigate the performance of the FSU. DNV (2011) recommends a ballast compartment with damage penetration zone of 1.5 m in width direction with a unit length. Constant heel angle of nine degree appeared in the FSU to simulate the flooded condition. To explore the dynamic behaviour of the FSU in detail, nine different angles of incident waves from zero to 360^0 with 45^0 increments are selected.

In this study *OrcaFlex* software is employed to conduct the hydrodynamic analysis. For each angle of attack, ICNW wave profile is inputtted manually in the software to conduct the simulation process. The obtained time-domain EDP data, such as roll response, is exported to the *MATLAB* software for determination of the probability distributions. For each simulation, the minimum and maximum value of roll motion responses are monitored to recognize the most extreme cases in which the results exceed operational and survival limits. To understand the variation of FSU performance in different scenarios and storm angles of attack, the results are illustrated in a polar plotted in Figure 4.7. As shown in the figure, the maximum roll angle of the intact structure for most of the angle of incident waves will be about 12º, which does not significantly exceed the safety limits (9 degrees). However, in a flooded FSU, both maximum and minimum roll angles exceed the survival limit resulting in an unsafe condition for the crew on-board. It is clear from the figure that 45^0, 270^0 and 180^0 are the critical angles of attack for a flooded structure. For this reason, in the developed BN represented in Figure 4.6, these three angles are considered for flooded condition and correspondingly only one angle is assigned for intact condition. The probabilistic analysis of hydrodynamic response, required for conducting risk analysis and decision-making, are explained in more detail in the following section.



H_s	Long-term probability distribution of significant sea wave
H_{Storm}	Probability of different level of storm condition encountered by ICNW profile
FR45/180/270	Flooded response in 45, 180 and 270 degrees
FU45/180/270	Flooded utility in 45,180 and 270 degrees
FD45/180/270	Flooded decision in 45, 180 and 270 degrees
IR45	Intact response in 45 degrees
IU45	Intact utility in 45 degrees
ID45	Intact decision in 45 degrees

Figure 4.6 Developed Influence diagram for risk assessment and decision making of a Floating Storage Unit encountering storm

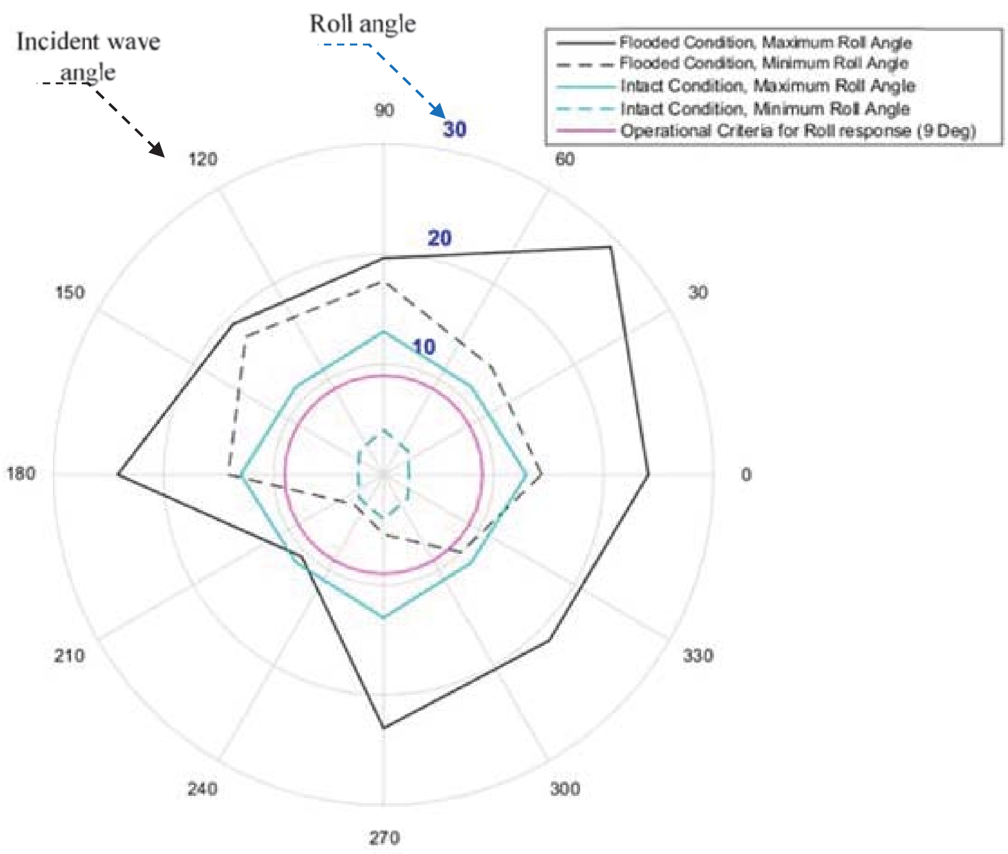


Figure 4.7 Roll motion of FSU subjected to ICNW storm profile from different angle of incidents

4.6.4 Define Probability Distribution of Stochastic Variables

As a requirement of any risk assessment and probabilistic decision-making process, it is essential to determine the performance of the FSU subjected to ICNW storm profile in probabilistic terms. The results from this part of the study are used for implementing the BN and completing the Conditional Probability Tables (CPT) in the network. Firstly, extreme values of storm wave height (H_{Storm}) for each different step in the ICNW profile should be estimated. Based on the description of Eq. (4.1) in Section 4.2, the k^{th} specific step is dependent on the characteristics of the k^{th} sea state. Consequently, storm wave heights are dependent on the significant wave height (H_s) outlining the associated sea state spectrum $S_k(\omega)$. Based on this concept the CPT for node H_{storm} is completed for each level of storm. For this purpose, each step in ICNW profile is fitted to Generalized Extreme Value (GEV) distribution using (MLE) method ensuring that the possible extreme values are captured. The obtained Probability

Density Functions (PDF) for significant wave heights and the PDFs of extreme wave amplitudes during storm are presented in Figure 4.8 and the data is summarized in Table 4.3.

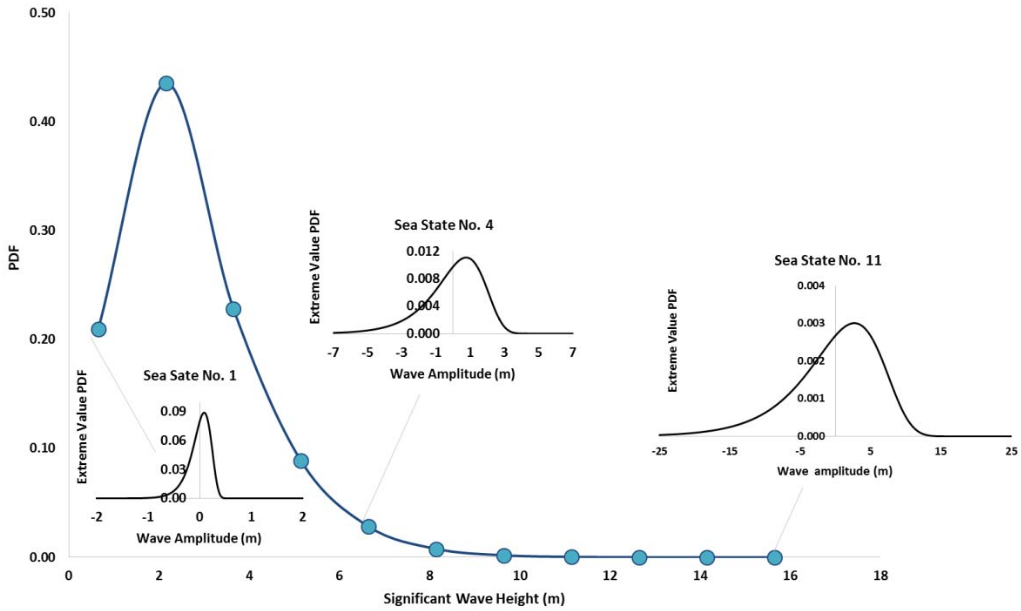


Figure 4.8 Long-term PDF of significant wave heights (blue line), and PDFs of storm wave amplitudes (black lines) obtained from ICNW profile

Probability distribution of the structure's roll angle is computed using the time-domain simulation data obtained in section 5.1.1, and considering the most critical scenarios in the performance of FSU is highlighted in Figure 4.7.

It is necessary to find the most suitable PDF that accurately represents the stochastic data. Moreover, when a rare accident problem (such as extreme roll angle in this study) is of interest, special attention is needed to predict the response of the structure which also has a small probability of occurrence. In previous studies, H Chen (2003); Diznab et al. (2014) recommend that GEV distribution is the most suitable function for predicting the long-term characteristic of a marine structure's response under extreme loads. However, for this study, GEV failed to provide an accurate prediction of the PDF according to stochastic time-domain data. The reason is that t-Location scale distribution shows better agreement for heavier tail functions to model more realistically phenomenon such as the stochastic process of the present study. In order to find the optimum case, a number of distribution functions were explored and MLE method was applied to find the distribution parameters such as shape and scale of each case.

Table 4.3 Conditional probability of extreme wave heights for different levels of ICNW storm profile (conditioned on significant wave heights

$p(H_{Storm}|H_s))$

	Time (sec)										
Significant Wave Height (m)	t<100	100-200	200-300	300-400	400-500	500-600	600-700	700-800	800-900	900-1000	1000-1100
>15.65	0	0	0	0	0	0.0001	0.0001	0.0000	0.0004	0.0031	0.0032
14.15	0	0	0	0	0	0.0002	0.0002	0.0000	0.0006	0.0031	0.0031
12.65	0	0	0	0	0	0.0005	0.0005	0.0000	0.0011	0.0049	0.0049
11.15	0	0	0	0	0	0.0011	0.0011	0.0001	0.0022	0.0078	0.0078
9.65	0	0	0	0	0	0.0025	0.0025	0.0004	0.0044	0.0124	0.0124
8.15	0	0	0	0.0002	0.0001	0.0056	0.0056	0.0013	0.0088	0.0225	0.0225
6.65	0	0	0.0001	0.0011	0.0007	0.0126	0.0126	0.0041	0.0175	0.0545	0.0545
5.15	0		0.0008	0.0048	0.0038	0.0289	0.0289	0.0125	0.0434	0.1237	0.1237
3.65	0	0.0003	0.0068	0.0215	0.0188	0.1084	0.1084	0.0433	0.1532	0.2067	0.2067
2.15	0.00000335	0.0136	0.0628	0.1670	0.1362	0.3352	0.3352	0.2876	0.3325	0.2664	0.2664
<0.65	0.99999665	0.9861	0.9296	0.8053	0.8403	0.5048	0.5048	0.6505	0.4357	0.2928	0.2928

comparison between GEV and t-Location Scale distribution is shown in Figure 4.9. It is clear that GEV has failed to model the occurrence probability of roll, particularly for extreme responses (roll angle > 20^o) caused by the storm while t-Location scale distribution performs better at modelling those responses. Although the shape parameter of the GEV is approximately the same as t-location scale distribution, which is 18 degree, the lack of precision of the scale parameter in GEV cause the graph fail to follow the true trend of the simulation data. Similarly, the response data for 180^0 and 45^0 of incident wave angle is fitted to t-Location scale distribution from which the obtained PDFs are presented in Figure 4.10, respectively. Table 4.4 also summarizes the t-Location Scale parameters estimated by MLE to fit simulation data of flooded condition. The table describe the fact that the expect degree freedom of the heeling of the vessel in a flooded condition will fluctuate on approximately around 18 degree during the storm condition. Since the structure is considerably large compare to the incident wave, then the vessel is more likely to keep the level of deviation from its mean value of 18 degree. It cause that the shape parameter of the distribution limits to number of one. That is the graph more likely to follow a sharp shape around the expected value of the distribution. In order to investigate the effect of damage on the performance of the structure, a comparison of extreme roll responses between flooded and intact condition for the most critical scenario (45 degree as illustrated in Figure 4.7) is conducted and represented in Figure 4.10. As shown in this figure, the range of roll angle in intact condition is considerably smaller than the variations in flooded condition. The range of rolling motion in the intact condition is less than 15 degrees, however, in a flooded condition it is anticipated to be more than 20 degrees. That is, the possibility of encountering much larger roll angles in the extreme condition will increase drastically for a flooded structure.

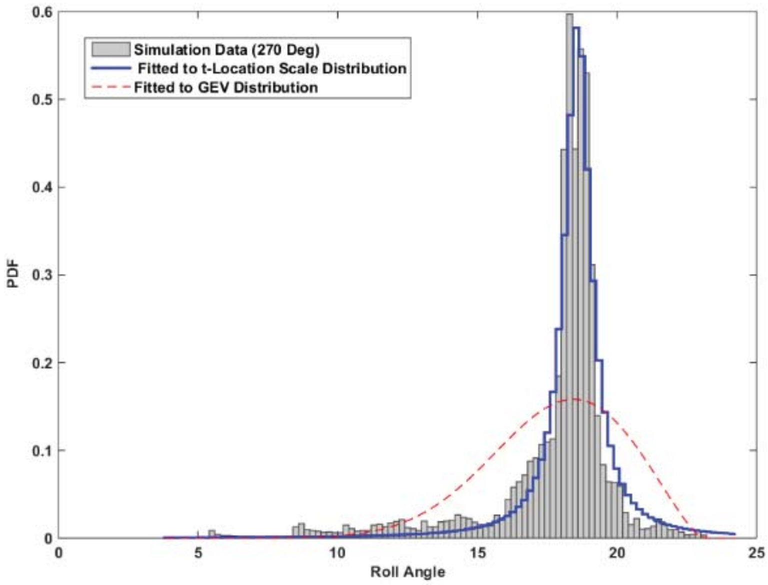
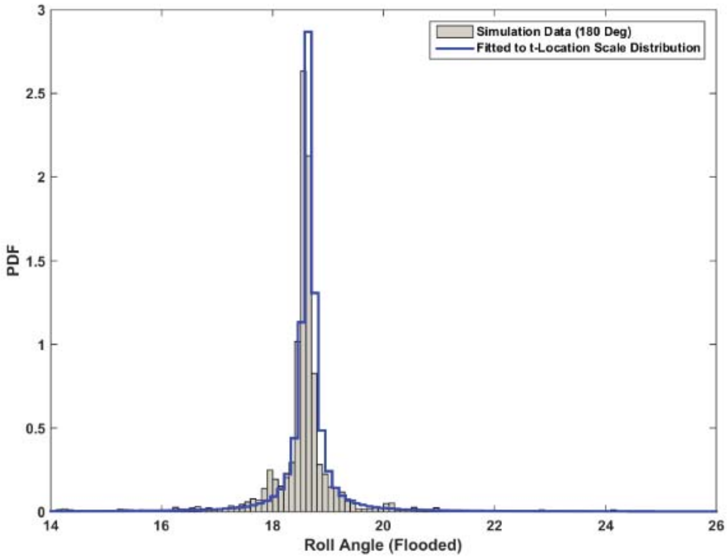
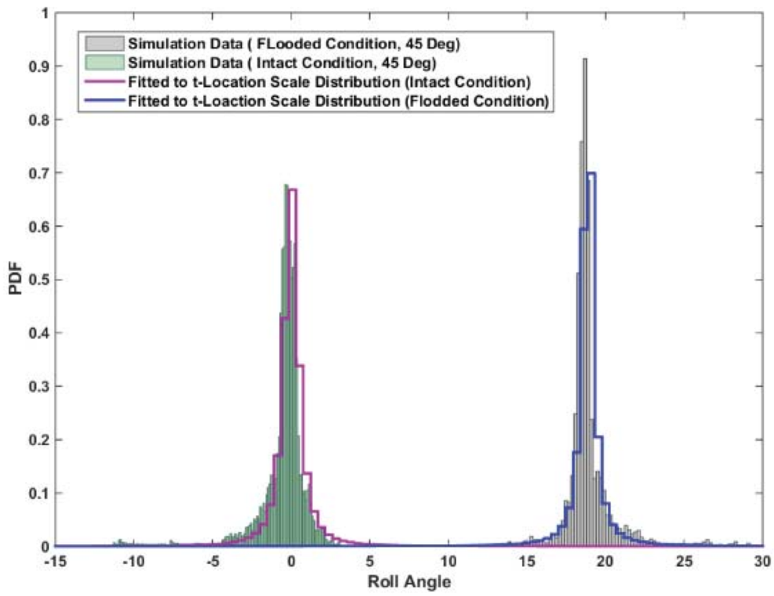


Figure 4.9 Estimated PDF for roll angle of a flooded FSU subjected to storm with 2700 of incident wave angle. A comparison between GEV and t-Location Scale distributions are provided.



(a)



(b)

Figure 4.10 Estimated PDF for roll angle of a flooded FSU subjected to storm with 180^0 of incident wave angle (a), and 45^0 of incident wave angle in both flooded and intact condition (b).

Table 4.4 Parameters of t-Location Scale Distribution (flooded condition)

Direction	Location parameter	Scale parameter	Shape parameter (Degree of Freedom)
270	18.6663	0.4136	0.9182
180	18.586	0.1074	0.8756
45	18.6596	0.3572	1.1055

4.6.5 Probabilistic Model and Decision Making Scenario

Estimated probability density function of roll angle are fed to the BN nodes, such as node FR45. To fill the utility and decision nodes such as FU45 and FD45, it is necessary to define the criteria that identifies the level of risk in each storm condition and possible extreme roll response of the FSU. According to the survival limit presented in Table 4.2, this criterion is a roll angle of nine degree, $\theta_1 = 9^0$. If the FSU's roll angle is lower than this, the best action is to halt the operation. However, if the roll angle exceeds this limit, then the system is not tolerable for the crew on board. Therefore, they should either request help or evacuate the unit. To make this clear, to find the best action as the level of storm becomes more severe, another criterion needs to be defined. According to (IACS 2012), the range of stability (RoS) in damage condition for floating unit is described as:

$$RoS = \theta_m - \theta_s \geq Max\left((7^0 + 1.5\theta_s), 10^0\right) \tag{4.5}$$

Where, θ_m is the maximum angle of positive stability (maximum angle of positive stability in intact condition for this floating unit is $\theta_m > 50$), and θ_s is the static angle of inclination after damage which is nine degrees in this study (See **5.1.1**). Therefore, the second criterion is assigned as $\theta_2 = \theta_m$. If the FSU roll angle exceeds θ_m in any scenario, then the vessel is about to capsize. Therefore, humans on-board should evacuate the vessel urgently rather than asking for help. Considering these aspect, three alternatives are defined for decision nodes: a) halt the operation and stay if $\theta < \theta_1$; b) request help to be picked up by helicopter or vessel if $\theta_1 \leq \theta < \theta_m$; c) evacuate the floating system urgently as the structure is about to capsize if $\theta \geq \theta_m$.

To compute the expected utility, these criteria were taken into consideration to assign for utility nodes. The values are selected based on the decision alternatives and possible losses according to the random behaviour of the vessel in storm condition. The cost associated with each decision alternative is estimated based on data available about the technical characteristics of the structure, as well as the price and cost details of operational actions such as request for help from onshore (Počuča 2006). The operational cost of such structures is mainly divided into six categories including fuel and consumables, crew salary, lubes and stores, maintenance cost, insurance and administration (Kay et al. 2011). However, in the case of decision making about survivability of the structure, other costs such as the rescue cost and the loss of capital due to evacuation need to be considered. In the present study, the cost profile is carefully derived from the accidents and operational databases and consultations with the experts in the field (Kay et al. 2011; Stopford 2009; Zei 2006). This resulted in assigning -\$1k, -\$10k and -\$$10^5$k for the cost of halting the operation, requesting help, and evacuating the facility, respectively. Since this study is focused on human safety on-board, any fatalities result in financial loss of \$$10^9$k according to the total cost associated with value of life recommended by Kip Viscusi (2005). This value is applied to justify an investment of a protection measure to avert the loss of a life and the material loss up to that order to prevent a life lost.. Therefore, due to saving human life as a priority compared to other associated cost; the value of human loss is considered to be a notably larger value. This will demonstrate that in the final estimation of maximum expected utility, a higher level of human safety will be achieved. Consequently, the expected value of each decision alternative is computed based on the occurrence probability of extreme roll response and utility values assigned (see Eq. 4.4 and Figure 4.6). A comparison of the estimated expected values of all decision alternatives for different incident storm angle of attack are presented in Figure 4.11. As illustrated in the graphs, if the floating unit is in intact condition, it can tolerate all ranges of the storm condition, therefore there will be no concern about staying on-board. On the other hand, in the case that the structure is flooded, the safety of the crew is dependent on the wave angle of attack. The results show, if the storm attacks the structure with angles of 45° and 270°, the captain should request help as the storm intensity is around a significant wave height of 5.15 m. Accordingly, when the storm increases its level to H_s= 8.15m, the crew should evacuate the vessel urgently. The situation is more flexible for the case that a flooded structure encounters the storm from the angle of 270°. The crew can stay on-board while they observe significant wave heights of 8.15 m, nevertheless they should request help to survive the severe condition. When the storm passes the wave height of H_s=14.15m, the crew should evacuate the vessel to save their lives.

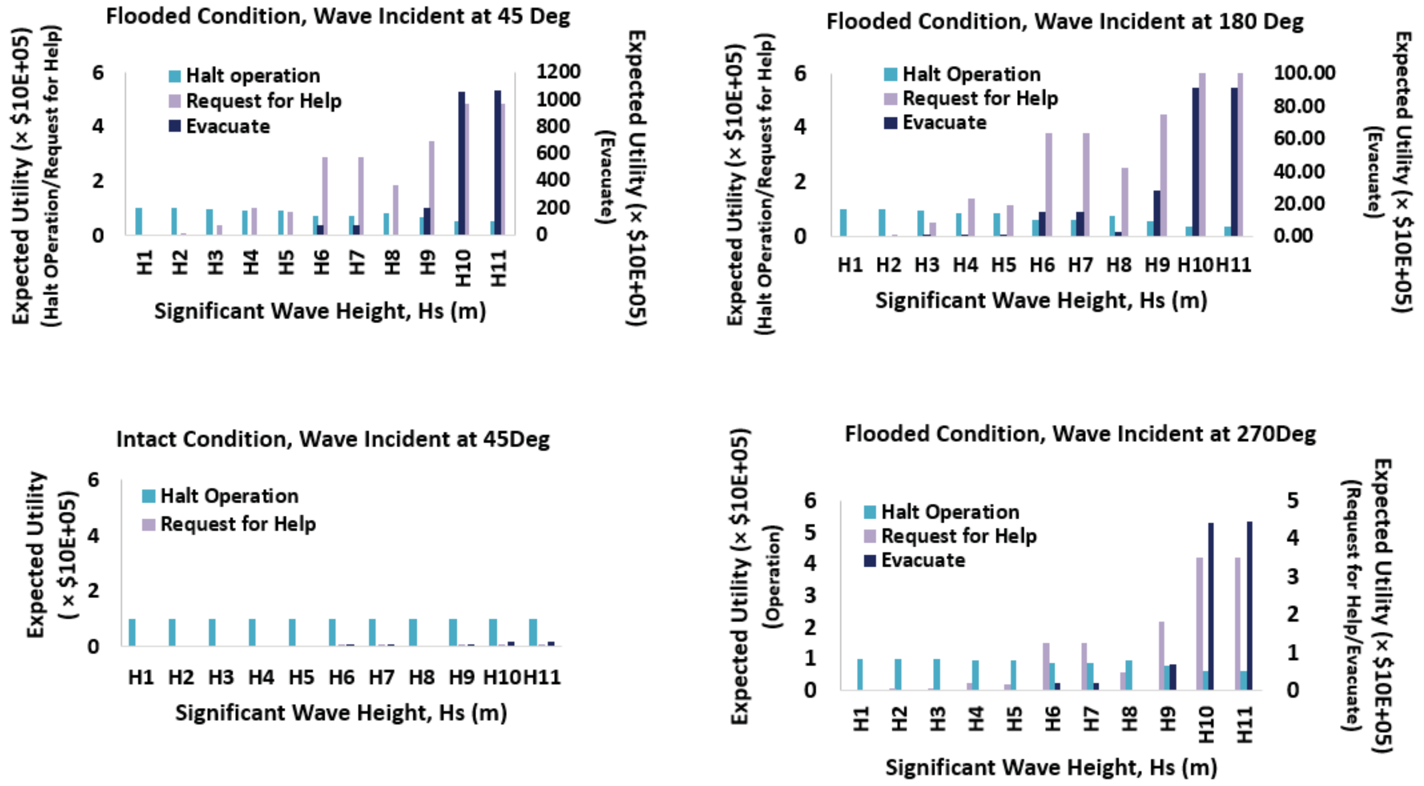


Figure 4.11 Expected utility of each decision alternative (halting the operation, requesting for help and evacuating the facility) under different storm levels and angle of incident waves

4.7 Conclusion

A methodology is proposed here to assist in efficient and robust decisions to improve safety of the marine structures in evolving operational conditions. The methodology is comprised of three main steps. Firstly, the hydrodynamic analysis is conducted upon replicating storm through an intensifying wave train function. This approach has the advantage of reducing computation cost of simulations. Second, the appropriate probability distributions of each level of storm and its stochastic parameters are estimated and the performance of floating structure is assessed through a Bayesian approach. The developed BN is then extended into an ID, which assists in quick and robust decision-making. The application and effectiveness of the proposed methodology is demonstrated through simulating an FSU in storm condition with different angles of attack. The results of the analysis indicate that the most critical incident wave angles are 45^o, 180^o and 270^o degrees. In a non-flooded condition, the structure will be safe in the storm, however it is necessary to halt the operation. For a flooded FSU, evacuation is the optimum decision alternative if the wave heights exceed H_s=8.15m for the incident wave angles of 45^0 and 180^0, and H_s=14.15m, for 270^o. These observations highlight the proposed methodology be used as an effective tool for quick and robust decisions. It incorporates the uncertainty associated with the dynamic behaviour of a floating structure and also the stochastic nature of operational and marine structure response variables. This methodology could be integrated with the e-navigational tool to ensure safety at sea.

5. Dynamic Reliability Assessment of Ship Grounding Using Bayesian Inference

Abstract

The significant increase in the demand for shipping transportation using large vessels in restricted waters, such as cruising cargo vessels in channels, draws worldwide maritime industries' attention to mitigating potential grounding risks. Safer ship navigation requires a more accurate prediction tool to estimate the likelihood of a ship striking the seabed. This study presents a safety framework for under keel clearance failure analysis of vessels crossing shallow waters. The developed methodology can be applied by the designers, operators and port managers to maintain their shipping fleets operating at an acceptable level of grounding safety. A Hierarchical Bayesian Analysis is applied to estimate the probability of touching the seabed based on the results of dynamic under keel clearance obtained from time-domain hydrodynamic simulations. To illustrate the application of the proposed method, the performance of a large vessel is assessed when entering the Queensland coastal zone with maximum water depth of 12 m. The framework suggests that for a safe navigation with maximum failure probability of 3×10^{-5} , the vessel should cross the passage at a speed lower than 3 m/s where the maximum tolerable incident wave height is 0.5 m.

Keywords: Hierarchical Bayesian analysis, Under keel clearance, Hydrodynamics, safety, Reliability, grounding failure

5.1 Introduction

By increasing the capacity of a shipping fleet, both in size and quantity, industries are more attracted to minimizing the grounding risk of shipping operations particularly in restricted waters. Ship grounding phenomenon accounts for one-third of commercial ship accidents highlighted as a major risk in marine transportation by previous researchers (Brown et al. 1997; Jebsen and Papakonstantinou 1997; Mazaheri et al. 2014). About 20% of all tanker losses between 1987 and 1991 (Brown et al. 1997), and 47% of all accidents of large Greek vessels from 1992 to 2005 were due to grounding (Samuelides et al. 2009). Proposing a reliable framework is essential for increasing the level of safety for ship navigation in shallow waters without compromising the loading capacity of the fleet. That is, developing a methodology is essential to determine the minimum Under Keel Clearance (UKC) of the ship that will avoid leading to a grounding accident. In the literature, several concepts and predefined formulae are proposed for determining the squat of a ship that sails in restricted or open water, amongst them three main approaches are singled out including theoretical (Gates and Herbich 1977; T. P. Gourlay 2000; T. Gourlay 2008), empirical (Barrass and Derrett 2011; Mazaheri et al. 2014; Moustafa and Yehia) and numerical methods (Europe 2006; T. P. Gourlay 2000; Sergent et al. 2015). Most of these researches are deterministic and do not consider the uncertainty associated with the parameters involved in predicting the UKC of the vessel as a function of time. The dynamic UKC can in turn assist in the assessment of Touching Bottom Probability (TBP) and provide the potential for risk assessment of very large ships (VLS) moving along a shallow passage. The factors that influence the DUKC of the ship, such as the speed, should be statistically analysed. A great deal of research has been conducted to develop risk-based methods for minimizing the probability of failure during ship voyaging time. However, these methods assume that the stochastic process is observed as a renewal process, hence Poisson assumption is adopted for modelling the ship TBP (Gucma 2004; N. Quy et al. 2006; N. M. Quy et al. 2007; Gucma and Schoeneich 2008;). N. Quy et al. (2006) and N. M. Quy et al. (2007) provide a parametric modelling method for safety policy improvement of ships entering shallow waters, assuming that the grounding accidents follow a Poisson process. Gucma and Schoeneich (2008) applied a Monte Carlo approach to assess the probability that a ferry passes its safe zone in regards to UKC. Their statistical method uses a large number of trial tests on the manoeuvring performance of various vessel types in different navigation conditions. However, based on the assumption of a renewal process, the intervals between each failure event (inter-arrival times) are independently and identically distributed (*iid*), while this can make the analysis questionable. It is not a true assumption to accept that the failure rate will be independent of time. In reality, the DUKC record of the ship for the i^{th} time-step is dependent on the value in time-step t_{i-1}, which conflicts with the assumption of a constant failure rate for the homogeneous Poisson process. Moreover, considering time dependency of the simulation data in a stochastic process is not a straightforward procedure for constructing a probabilistic model. Recent advances in Bayesian statistical methods, namely Hierarchical Bayesian Modelling (HBM) that can be carried out using open source Markov Chain Monte Carlo (MCMC) software packages such as OpenBUGS (Lunn et al. 2000), have brought them to a wider audience for solving complex engineering problems (Kelly and Smith 2009). These methods are widely used in probabilistic risk assessment (PRA) because of their ability to provide useful estimation of model parameters when either data are sparse or the correlation between them is difficult to perceive (Abbassi et al. 2017; El-Gheriani et al. 2017; Kelly and Smith 2009; Friis-Hansen 2000; Siu and Kelly 1998). In risk analysis, there is a need to adopt data from different sources with varying levels of detail and incorporating the uncertainty that accompanies the data. HBM can address uncertainty among the aggregated data for each event through generating an informative prior distribution and possible observations for the event's parameter of interest (El-Gheriani et al. 2017). There have been many applications of Bayesian inference that demonstrate the advantages of this method in PRA. Examples include risk-based maintenance planning, deterioration process and component failure analysis (Arzaghi et al. 2017; Bhandari et al. 2016; Khakzad et al. 2014; Straub 2009), reliability assessment of marine structures and multi-criteria decision making (Abaei et al. 2018c, Abaei et al. 2017; Luque et al. 2014).

This paper aims at developing a methodology for reliability analysis of the vessels transiting a shallow waterway, while considering the time dependency of the stochastic motion responses. The results derived from this study provide the necessary information for any risk mitigation strategies and decision support tools that are concerned with improving the safety of marine transportation in a port area. A number of time-domain simulations are carried out to evaluate the hydrodynamic performance of the vessel at different speeds and in random sea waves. Nonhomogeneous Poisson process (NHPP) is adopted to quantify the number of times that the vessel passes its safety limits of safe ground touching. MCMC is then applied to predict the TBP using Bayesian Inference. To demonstrate the application of the proposed methodology, a VLS approaching the Northern coast of Queensland is considered as a case study.

5.2 Dynamic Under Keel Clearance

The motion of a vessel in shallow water causes a mass of fluid to be pushed away at the front of the hull. This amount of water must flow back under the vessel and along the sides of the hull resulting in the acceleration of flow particles and in turn a significant pressure drop. This phenomenon leads to a reduction in keel clearance of the vessel. Compared with the neutral position of the stationary vessel, represented in Figure 5.1, the motion causes the hull to sink deeper into the water with a slight trimming.

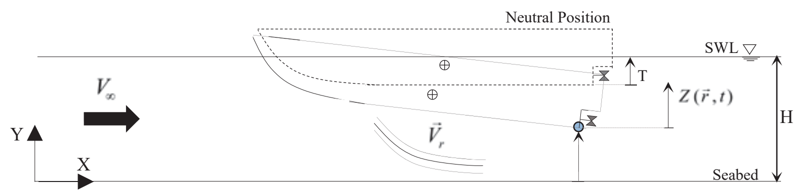


Figure 5.1 Schematic representation of sinkage and trimming of a forward moving vessel in shallow water

The algebraic sum of both, sinking and trimming is known as squat. Dynamic under keel clearance (DUKC) of a vessel is described as the clearance left from the static draft after subtraction of squat caused by the forward motion of the ship (Galor 2008):

$$DUKC(\vec{r},t) = H - T - Z(\vec{r},t) \tag{5.1}$$

where $Z(\vec{r},t)$ is the dynamic squat of the vessel, H is the water depth and T is the static draft. These parameters can be driven either from theoretical, empirical or numerical approaches as recommended by Sergent et al. (2015). However, an empirical formula will not be applicable for all types of vessels and operational conditions (Briggs et al. 2013), and theoretical approaches cannot provide a realistic estimation of DUKC due to a number of assumptions needed for developing the model (T. P. Gourlay 2000; Sergent et al. 2015). Therefore, a numerical model is essential to evaluate the hydrodynamic responses of the vessel in every degree of freedom and finding the absolute local sinkage (shown as a blue circle in Figure 5.1). To understand the dynamic behaviour of a ship's UKC, the following equation developed and based on Newton's second law will be considered (Sergent et al. 2015):

$$m\frac{d^2\vec{r}}{dt^2} = -mg + \int_{Hull} P\,\vec{n}\,\vec{e}_z\,ds \tag{5.2}$$

where m is the mass of ship, g is gravity acceleration, ds is a surface element of the ship hull, P is the pressure of the flow, $\vec{n}$ is the normal vector on the wetted surface of the ship, $\vec{e}_z$ is the direction of the forces exerted in the *heave* degree of freedom. The continuity equation yields the velocity of the flow under the keel as:

$$V(\vec{r},t) = \frac{V_\infty H}{\mathrm{DUKC}(\vec{r},t)} \tag{5.3}$$

where, V_∞ is the far-field flow velocity and $\vec{r}$ is the position vector of (x, y, z). The pressure of the flow, P, will be estimated using Bernoulli equation (Sergent et al. 2015):

$$P(\vec{r},t) = \rho g\left(H - \mathrm{DUKC}(\vec{r},t)\right) + \frac{\rho}{2}V_\infty^2\left(1 - \frac{H^2}{\mathrm{DUKC}(\vec{r},t)}\right) \tag{5.4}$$

Therefore, a time-domain numerical model needs to be employed to simulate ship squat. Different models are available for simulating the scenario. For instance, Gourlay (2000) and Debaillon (2005) developed a finite difference and finite element model respectively for evaluating dynamic behaviour of the vessel. N. M. Quy et al. (2007) developed a 3D-diffraction model using HARAP software to estimate the response amplitude operator of the vessel operating in random sea waves. Among them, 3D-Diffraction is suggested for hydrodynamic analysis of large structures as the inertia force is dominant compared to the drag force, and the computational cost is more efficient (Karimirad 2011). Hence, in this study, a time-domain 3D-Diffraction model is adopted from Abaiee et al. (2016) for predicting response of the vessel under random sea waves. For this purpose, AQWA program (Manual, 2009) was used for processing the time-domain 3D-Diffraction simulation and evaluating performance of DUKC of the vessel in different environment conditions. This approach is appropriate for large-volume structures where the incident waves tend to be affected by the structure and where part of the encountering waves will be diffracted by the structure and part of them will be radiated (Abaiee et al., 2016).

5.3 Hierarchical Bayesian Modelling

Performing any kind of statistical inference starts with data. Data is defined as the observation values of a stochastic process that may incorporate various sources of uncertainty. Whatever is obtained from the evaluation, manipulating or organizing data, is referred to as "Information" which leads to improving our "Knowledge", while "Knowledge" is what is known from gathered information. Finally, the process of obtaining a conclusion based on what one knows, is regarded as "Inference" (Kelly and Smith 2009). HBM is a probabilistic approach that allows the organisation of inference based on real-world observations into information (Kelly and Smith 2009; Siu and Kelly 1998). In the present paper, Bayes' theorem is considered for carrying out inference (Kelly and Smith 2009):

$$\pi_1(\theta \mid x) = \frac{f(x \mid \theta)\pi_0(\theta)}{\int_{\theta} f(x \mid \theta)\pi_0(\theta)\, d\theta} \tag{5.5}$$

where θ is the unknown parameter of interest, $f(x \mid \theta)$ is the likelihood function, and $\pi_1(\theta \mid x)$ is the posterior distribution. In the Hierarchical Baysian framework, multistage prior distributions defined for parameter of interest, denoted by $\pi_0(\theta)$ (Kelly and Smith 2009) can be calculated by:

$$\pi_0(\theta) = \int_{\Phi} \pi_1(\theta \mid \varphi)\pi_2(\theta) \tag{5.6}$$

Where, $\pi_1(\theta \mid \varphi)$ is the first-stage prior representing the population variability in θ; $\pi_2(\varphi)$ is the hyper-prior distribution representing the uncertainty in φ; φ is a vector of hyper-parameters e.g. $\varphi = (\alpha, \beta)$, while α and β are the shape and scale parameters respectively, of a Weibul distribution. The prior is developed using generic data collected from different sources (numerical simulations, experiments or collected from different industrial sectors). These result in an informative prior distribution, $\pi_0(\varphi)$, for estimating the posterior distribution.

HBMs are found to be more reliable in comparison to classical statistical methods, as they are able to incorporate various types of information, each having some sources of uncertainty, in the estimation process (Siu and Kelly 1998). As a subjective-based probability framework, it can assist in PRA by propagating uncertainties through complex models (Siu and Kelly 1998). Recently, studies were conducted to bring the application of HBM in PRA (Kelly and Smith 2009; Niu et al. 2015; Yang et al. 2013). Mostly, they generally proved the advantages of HBM for risk and reliability assessment of process engineering such as oil spill assessment and component failure analysis. In the present study, a methodology is developed using HBM for predicting the likelihood of ship grounding in restricted water.

5.4 Methodology: Ship Grounding Assessment

This paper aims at developing a practical safety assessment framework for estimating the TBP of vessels operating in restricted waters. This framework will assist the operators to maintain the UKC of a vessel out of its critical zone. The outcome of the proposed approach is the lessening of ship grounding risk and improving the safety of navigation in the port area. The proposed methodology consists of two steps as presented in Figure 5.2 and discussed in the following sections.

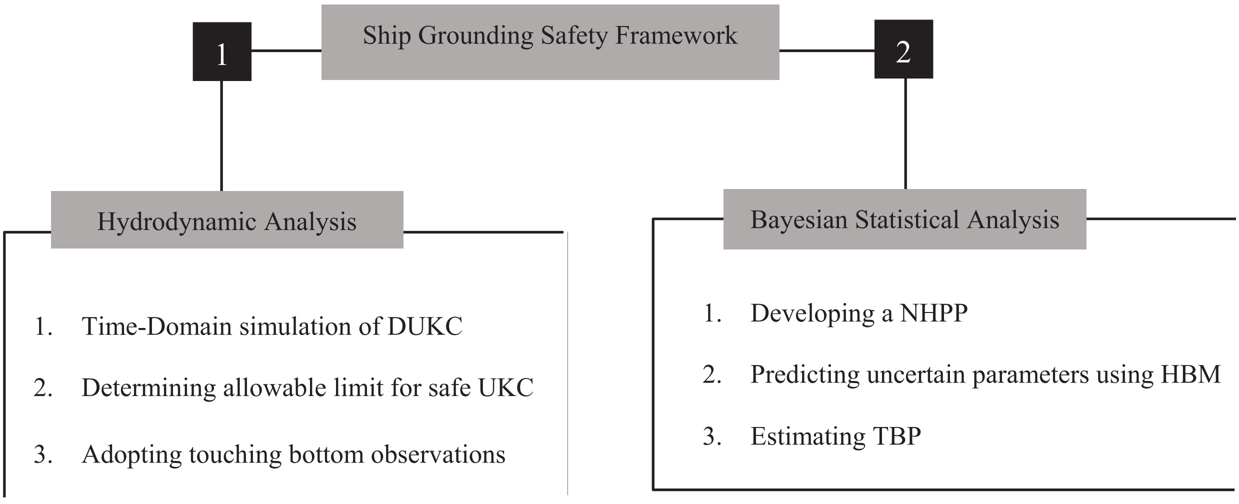


Figure 5.2 Different steps considered in the proposed methodology

5.4.1 Hydrodynamic Modelling

In order to develop a framework for safety assessment of ship navigation in shallow water, it is necessary to estimate the stochastic dynamic responses of the vessel in a random sea environment. This part of the methodology will assist in evaluating time-varying UKC along the entire voyage route from entering to leaving a shallow water area. The results will generate essential observation data for analysing the time and number of ship grounding events as the input to the second part of study which is failure assessment. For this purpose, a time-domain hydrodynamic simulation is employed for developing the stochastic DUKC function and the maximum local sinkage of the vessel (illustrated with blue points in Figure 5.3) given by Eq. (5.7),

$$\mathrm{DUKC}_{ij} = f(\vec{r}, t, V_s^i, H_s^j, H, L, B, T) \quad , \quad i = 1, 2, \ldots, n \ ; \ j = 1, 2, \ldots, m \qquad (5.7)$$

where, t is time, $\vec{r}$ is the location of local sinkage, V_s is ship speed, H_s is the encountered random wave heights, H is water depth and L and B are the length and breadth of the vessel. This function should be generated for the entire range of operational ship speed, V_s^i, and significant wave height, H_s^i, to enable the evaluation of all possible manoeuvring conditions of the vessel in shallow water. A safe clearance zone is defined to preserve ship's UKC in a safe condition during the voyage. That is, for each DUKC_{ij} an allowable Safe Limit (SL) is considered and observations of the time that the vessel enters the unsafe clearance zone (UCZ) is recorded. These observations are required as the input for the next step of the study which predicts the likelihood of ship grounding. The limits of UCZ are dependent on several factors related to under-keel clearance such as underwater obstructions, unclear layers of mud and the uncertainties associated with charted depth (Parker and Huff 2015). In most cases, the allowable UCZ is defined based on UKC management system for each port for arriving and departing vessels. For instance, the Australian Maritime Safety Authority (AMSA) recommends an UCZ equal to 10% of the actual water depth in the region, H (Tull 2006). In the present study, this recommendation by AMSA is adopted for determining the safe limit of each DUKC_{ij} record.

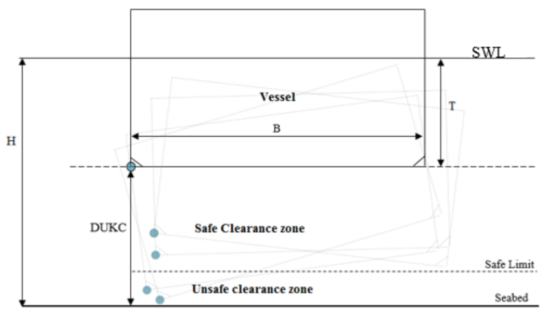


Figure 5.3 Graphical representation of DUKC model that generates the observations of grounding events (blue points represent the location of the keel with respect to several simulation times).

5.4.2 Grounding Failure Assessment

Upon obtaining the DUKC responses, a failure model is developed to estimate the likelihood of the vessel touching the seabed. The model is based on the assumption that for any inter-arrival time [t_i, t_{i+1}], the number of UKC points passing the SL are not identically independently distributed (*iid*). Therefore, the i^{th}-passage failure, known as the event where the vessel passes its SL for the i^{th} time in t_i , is dependent upon t_{i-1} in which the previous event has occurred. Based on this assumption, the failure rate $\lambda(t)$ is dependent on time and the simulation yields stochastic results that represent a nonhomogeneous Poisson Process (NHPP), accordingly the expected number of failures in any given time interval, [t_{i-1}, t_i], is given by Eq. (5.8):

$$E[\lambda(t)] = \int_{t_1}^{t_2} \lambda(t)\, dt \tag{5.8}$$

where NF is the number of failures that the vessel touches the seabed. Subsequently, an appropriate function must be specified for $\lambda(t)$ representing the NHPP. Some of the common forms for $\lambda(t)$ recommended in previous studies are power-law, log-linear and linear models (Chang 2001; Kelly and Smith 2009). For the proposed method, the power law function is considered for the failure assessment of DUKC due to its ability to predict the nonlinearity of random process more accurately when compared to the linear models (Kelly and Smith 2009) . This function is given by Eq. (5.9):

$$\lambda(t) = \frac{\alpha}{\beta}\left(\frac{t}{\beta}\right)^{\alpha-1} \tag{5.9}$$

This model can also subsume a constant failure rate assumption in the specific state where $\alpha = 1$. Therefore, the time to observe the *first*-passage failure event, given the power-law function for failure rate, follows a Weibull distribution with shape parameter α and scale parameter β (Ross 1976), stated in Eq. (5.10).

$$f(t_1) = \frac{\alpha}{\beta}\left(\frac{t_1}{\beta}\right)^{\alpha-1} \exp\left[-\left(t_1/\beta\right)^{\alpha}\right] \tag{5.10}$$

To estimate the parameters of α and β , HBM is employed for sampling the i^{th}-passage failure observations, represented by the blue points located below the SL in Figure 5.3. For each time interval [t_i, t_{i-1}], a conditional probability function must be defined to reflect the dependency of observation points on the previous failure events in each simulation (Ross 1976), as given by Eq. (5.11):

$$f(t_i \mid t_{i-1}) = f(t_i \mid T_i > t_{i-1}) = \frac{f(t_i)}{\Pr(T_i > t_{i-1})} \quad , \quad i = 2,\ldots,n \tag{5.11}$$

where T_i is the observation time of grounding event for the vessel with a specific voyage distance, S, and a ship speed, V_s. Eq. (5.11) is a truncated Weibulll distribution and the recommended likelihood function, by Kelly and Smith (2009), is defined as $f(t_1, t_2, \ldots, t_n \mid \alpha, \beta)$ in which α and β are the hyper parameters. OpenBUGS software is utilized to perform the MCMC sampling from the joint distribution of α and β to obtain the marginal posterior distribution of the hyper parameters. Although the aforementioned likelihood function is not pre-programmed into OpenBUGS, an aleatory model can be developed using a generic distribution function termed as "dlogik", as suggested by Kelly and Smith (2009). By defining parameter $\varphi = \log(\text{likelihood})$, Eq. (5.11) allows OpenBUGS to update the parameters in the likelihood function (phi), with a vector size of *n* with the samples of α and β from the prior distribution in Eq. (5.13):

$$\varphi = \log(\alpha) - \alpha \times \log(\beta) + (\alpha - 1)\log(t_i) - (t_n / \beta)^{\alpha} / n \tag{5.12}$$

where, t_n is the last observation of the grounding event in the simulation. The independent diffusive Gamma distribution is used for the prior distribution of hyper-parameters, as suggested by Kelly and Smith (2009) and given by:

$$\begin{aligned} &\alpha \sim Gamma(0.0001, 0.0001) \\ &\beta \sim Gamma(0.0001, 0.0001) \end{aligned} \tag{5.13}$$

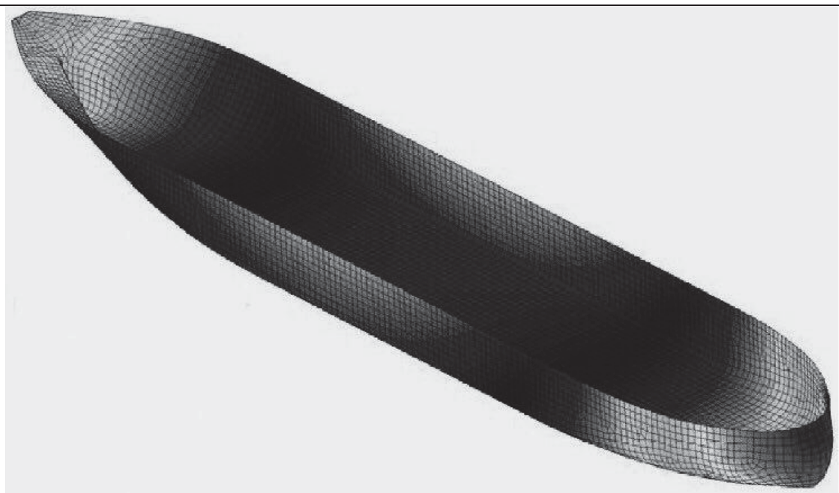
In Eq. (5.12) t_i is the i^{th} observation of the vessel keel passing SCZ shown in Figure 5.3. The MCMC sampling must be performed for $i=1,\ldots,n$ to estimate the updated posterior distribution of hyper-parameters (α, β). These distributions are then adopted to predict the probability of grounding based on a Weibull function. This process is repeated for each DUKC_{ij} record (each simulation) to investigate various failure conditions for the vessel to pass its SCZ during the voyage in restricted waters. This results in a failure probability distribution function for each operational condition enabling the improvement of safety in ship navigation.

5.5 Methodology Application: Case Study of a VLS in Queensland Waterway

To demonstrate the application of the developed methodology, the safety assessment of a VLS navigating in Queensland's coastal zones is considered as the case study. Approximately 80% of the Queensland population live in the coastal region which makes for a significant demand for shipping transportation using large vessels in this area (Caton and Harvey 2015). According to Hemer et al. (2007) the maximum observable significant wave height in the Queensland coastal zone is 1.0 m. Therefore, the DUKC_{ij} simulations in this study are carried out for two levels of significant wave height $Hs = [H_s^i] = [0.5 \;\; 1.0]\, m$ and four levels of ship speed, $Vs = [V_s^i] = [2 \;\; 3 \;\; 4 \;\; 5]$ *m/s*. This results in a total of 8 simulations, all performed for the maximum travel time, T_{max}. The geometry details of the VLS model with a figure of the ship hull used for hydrodynamic simulations in AQWA/ANSYS software are listed in Table 5.1.

Table 5.1 Geometry details of simulated VLS

Variable	Value	Unit
Water Depth (H)	12.0	m
Overall length (L)	205.0	m
Beam (B)	16.0	m
Loaded draft (T)	8.0	m
Radius of Gyration in Roll (from centre)	12.5	m
Radius of Gyration in Pitch (from centre)	21.0	m
Displacement	210000	ton
Centre of Gravity (m)	10.0	m
Block Coefficient	0.84	-



The heave response and DUKC for the first simulation (for V_S = 2.0 m/s and H_S = 0.5 m) predicted for a voyage time of T_{max}=2500 sec is illustrated in Figure 5.4. In this figure, the static under keel clearance (SUKC) is computed as z = -4.0 m. Based on the AMSA recommendations regarding the safety of navigation in restricted waters, a safety limit of $SL = -10.80$ m is specified for detecting the events where the vessel keel enters UCZ. These detections are adopted as the observations for the assessment of ship grounding as described in section 2.2. The observations from the DUKC records of simulations carried out for H_S = 0.5 m and the entire range of ship speed, V_S are illustrated in Figure 5.5. It is clearly shown in the figure that by increasing the ship speed, the number of observation points entering UCZ dramatically increases, from 5 points for V_S = 2 m/s to 49 points for V_S = 5 m/s. Also, the range between the first and the last observation time, $[t_1,t_n]$ becomes smaller for lower ship speeds. For instance, at V_S = 2 m/s the range is [985, 2111] sec, while it extends to [196, 2485] sec when the vessel cruises at V_S = 5 m/s.

The observations are then entered into the HBM for developing the likelihood functions and estimating the posterior distribution of Weibull parameters, α and β. The model for estimating the Weibull parameters (α,β), considered two chains in the MCMC modelling approach. Each simulation is performed with a total of 600E+03 iterations to predict the posterior distributions. Figure 5.6 shows the estimated posterior distribution of the shape parameter, α as well as the correlation between Weibull parameters (α,β) for ship speed of V_S =3 m/s and significant wave height of H_S = 0.5 m.

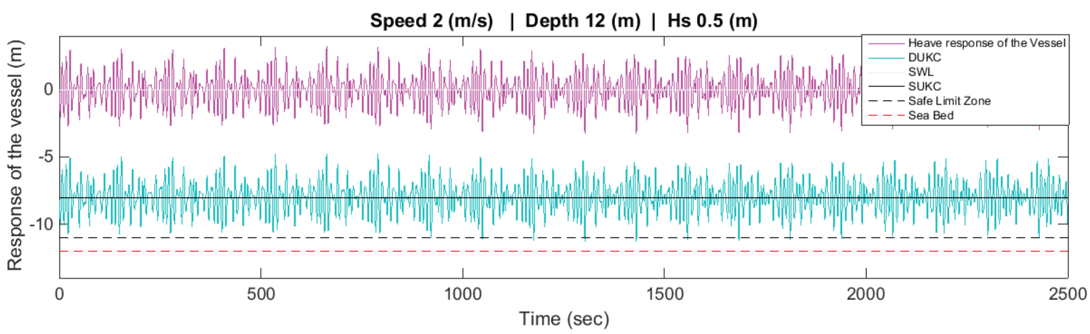


Figure 5.4 Time history of hydrodynamic responses (heave and local DUKC) for ship speed V_S = 2 m/s and significant wave height H_S=0.5 m.

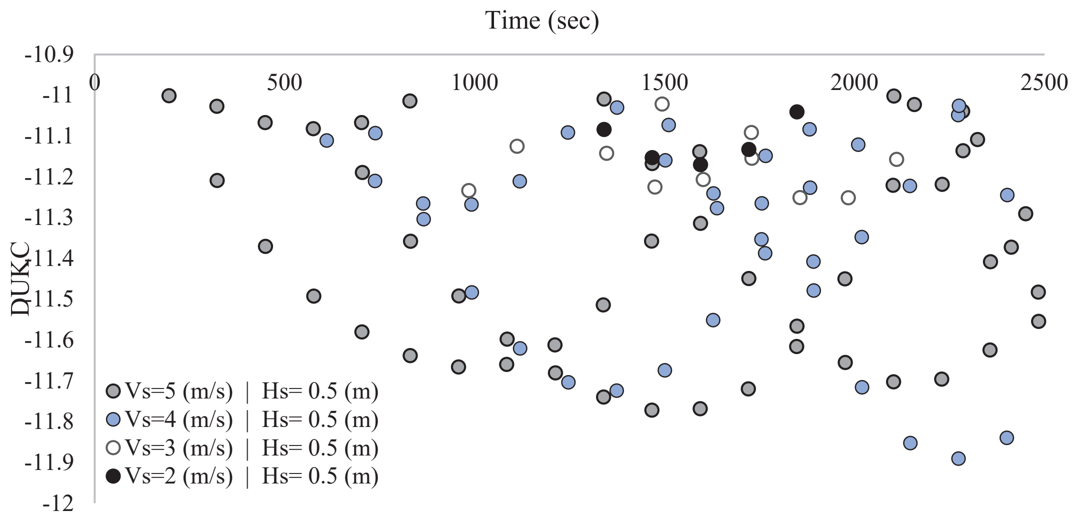


Figure 5.5 Observations of vessel keel passing the SL for ship speeds Vs =2m/s to 5m/s and significant wave height of Hs = 0.5m.

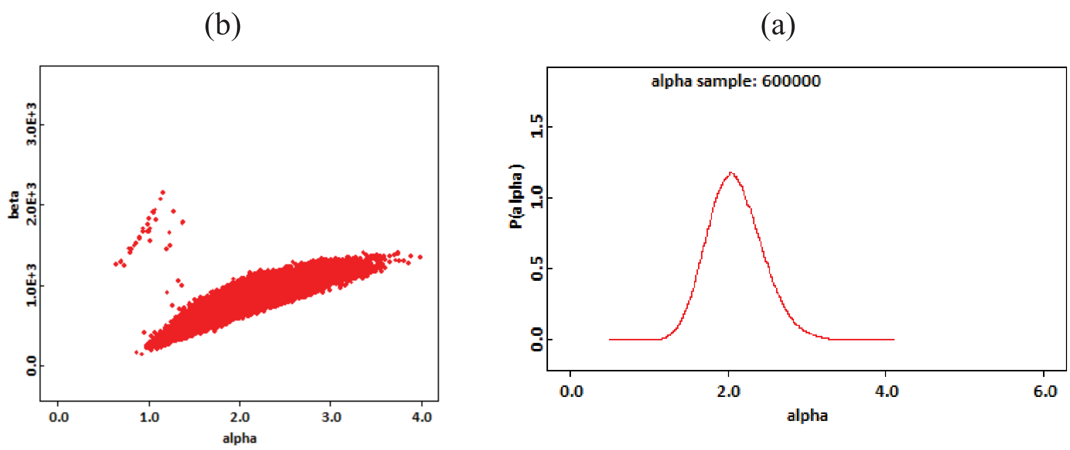


Figure 5.6 Posterior distribution of Weibull shape parameter α , graph (a) and the correlation between α and β , graph (b) for Vs =3 m/s and Hs = 0.5 m.

In Figure 5.6, the values of shape parameter for 2.5 and 97.5 percentile are $\alpha = 1.375$ and $\alpha = 4.949$, respectively. The expected value of alpha is estimated as $E[\alpha] = 2.989$ stands for 2.989, which is significantly higher than $\alpha = 1$ highlighting the importance of time-dependent assumption for failure rate of ship grounding (see Eq. (5.9)). The expected value of Weibull parameters for all vessel speeds and wave heights are listed in Table 5.2. It is found that shape parameter approaches $\alpha = 1$ as the sea environment becomes more extreme.

Table 5.2 Expected Value of Weibull Parameters predicted based on NHPP for different vessel speeds and incident wave heights

H_S= 0.5 (m)				
V_S (m/s)	2	3	4	5
α	5.105	2.898	2.091	1.985
β	1105	930.5	795	245.5
H_s= 1.0 (m)				
V_s (m/s)	2	3	4	5
α	1.1	1.02	0.9311	0.9884
β	305.5	264.6	213.9	67.28

The estimated probability of ship grounding for different ship speeds and significant wave heights are computed over a voyage time of T_{max} = 2500 sec. This time corresponds to a minimum voyage distance of 5 km for the ship transiting Queensland restricted waterway (Caton and Harvey, 2015) and the results are presented in Figure 5.7 and 5.8. It is found from these figures that any increase in the cruising speed of the vessel results in a lower expected time of grounding failure. For instance, in the sea states with H_S = 0.5m, the expected time of grounding failure for V_S = 2m/s and 5m/s are 0.217E+03s and 1.015E+03s, respectively. These parameters are predicted as 0.067E+03s for V_S = 2m/s and 0.295E+03s for V_S = 5m/s when the significant wave height is H_S= 1.0m. It is also observed that the variation in the grounding likelihood for different ship speeds will be decreased as the sea environment faces higher wave heights.

In order to examine the probability of First Time to Failure (FTTF) of the vessel in a particular passage, six voyage distances (S) are considered from the simulation results. A summary of the traveling time T, for different voyage distances and the ship speeds are listed in Table 5.3 and the predicted probability of FTTF of each case is illustrated as presented in Figure 5.9 and 5.10.

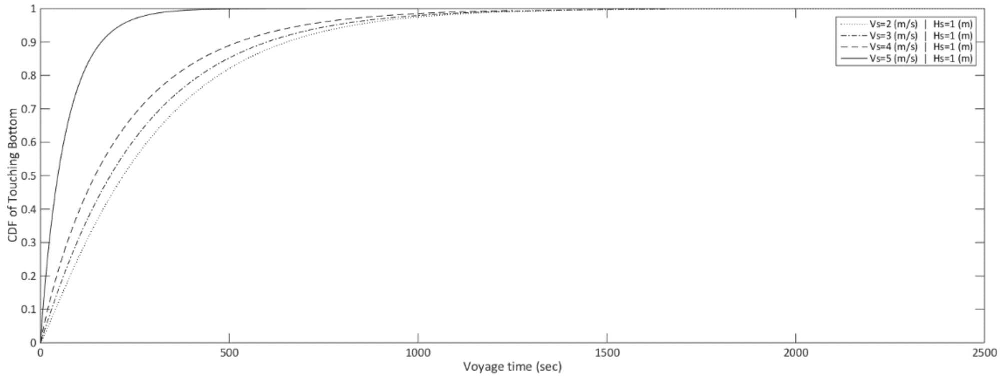


Figure 5.7 Probability of grounding accident for the VLS subjected to H_S = 0.5m and different ship speeds.

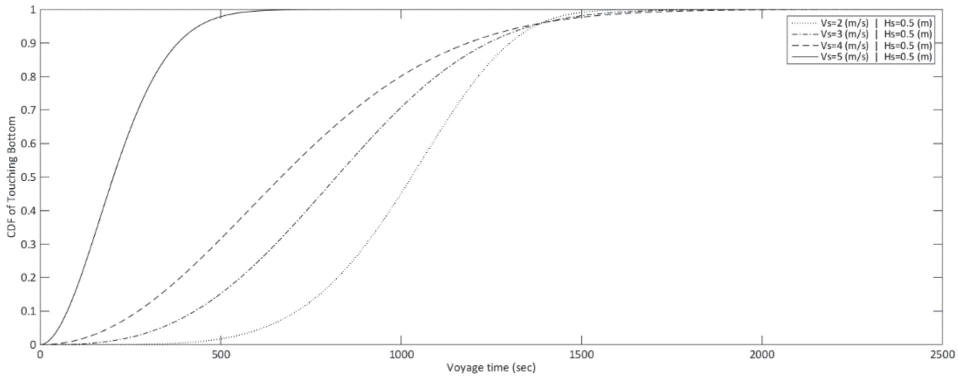


Figure 5.8 Probability of grounding accident for the VLS subjected to H_S= 1.0m and different ship speeds

Table 5.3 Travelling time of the vessel based on different ship speeds and journey distances

	Voyage distance *S* (m)					
	500	1000	2000	3000	4000	5000
V_S (m/s)	Time of travelling, T (sec)					
2	250	500	1000	1500	2000	2500
3	167	332	667	1000	1332	1667
4	125	250	500	750	1000	1250
5	100	200	400	600	800	1000

A comparison between the results in Figure 5.9 and 5.10 confirms that the ship is expected to have higher probability in shorter ranges of passage distance for higher ship speeds compared to the events observed at lower speeds. That is, for a vessel with a higher speed, the FTTF is predicted to be observed more in the earlier part of the voyage with a greater probability of touching the bottom, while this probability will decrease drastically by increasing the voyage distance. As an example, for a voyage distance of 500 m at a significant wave height of 0.5m, the probability of FTTF is estimated as 3.35E-03 and 1.04E-05 for ship speed of Vs=5m/s and 2m/s, while these probabilities change to 3.23E-03 and 1.58E-03 correspondingly, for H_S =1.0 m. It is observed from Figure 5.9 that at H_S=0.5 m at a cruising speed of 2 m/s the maximum probability of FTTF is estimated as p_{max} =1.68E-03 that is it is expected to occur at the voyage distance of 2000m while this probability is decreased to 0.95E-03 for Vs=5m/s. The results also highlight that the variation of probability of FTTF between different ship speeds dramatically decreases at longer distances. If it is considered that the allowable probability of grounding is $Z(\vec{r},t)$ (3 per 100,000 ship movements as recommended by Vrijling (1995), the results of the case study suggest that an acceptable level of safety can be achieved while navigating at ship speeds less that 3m/s and significant wave heights of lower than 0.5m, given the geometry details of the vessel as well as the water depth of 12 m. The presented results highlight that the proposed framework can model the grounding of the vessel more accurately in comparison to previous methods due to relaxing the assumption of a constant failure rate and considering the time dependency of the observed data. The method can be readily used by the operators and port management systems to improve the safety of the port operations as well as developing more effective risk mitigation policies for transitioning in restricted waters.

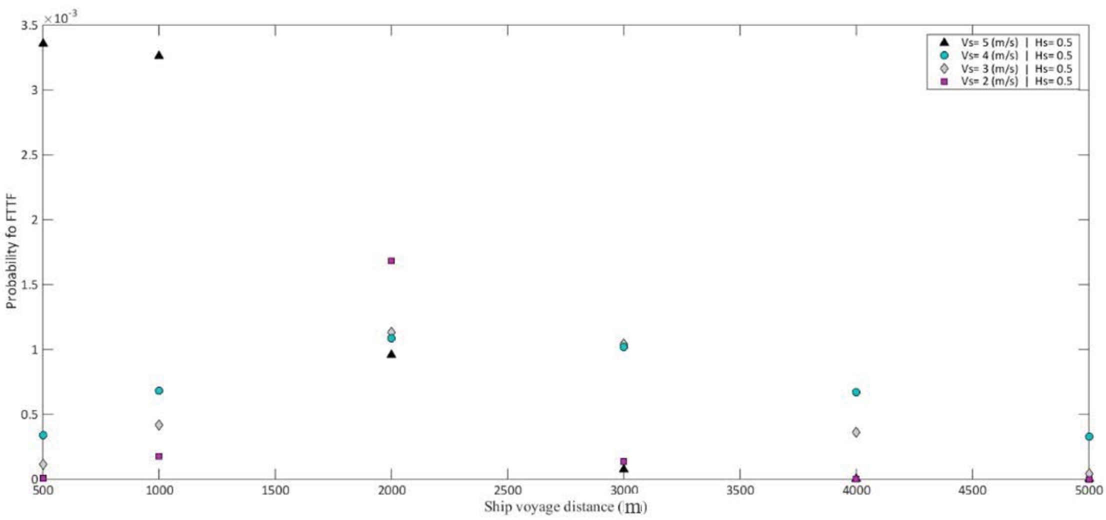


Figure 5.9 Estimated FTTF probability of grounding for a vessel cruising in different passages and speeds and subjected to a wave height of H_S= 0.5m.

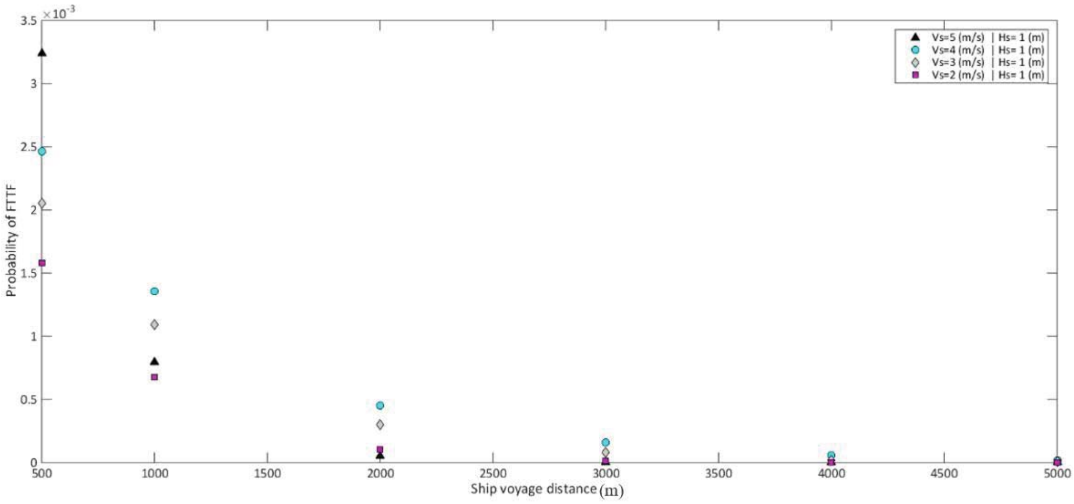


Figure 5.10 Estimated FTTF probability of grounding for a vessel cruising in different passages and speeds and subjected to a wave height of H_S= 1m.

5.6 Conclusion

The present paper proposes a methodology for predicting the grounding likelihood of ships cruising in shallow waters such as coastal areas. The developed framework integrates the hydrodynamic analysis of DUKC with a Bayesian predictive tool to achieve its objective. The hydrodynamic responses of a VLS are numerically analysed for different ship speeds and incident wave heights where the estimated DUKC results are adopted to develop the HBM. As a case study, the performance of the vessel was assessed when entering the coastal zones in North-East Queensland with a water depth of 12 m. It is observed that the predictions are highly dependent on ship speeds and sea states, highlighting the need for an NHPP model in ship grounding assessment. The results suggest that a vessel can safely operate in maximum incident wave heights of 0.5m with speeds lower than 3m/s while the probability of FTTF is maintained at less than $Z(\vec{r},t)$, which is recommended by the literature as the acceptable safety limit. The proposed framework can predict the grounding likelihood of a vessel more accurately by considering the time dependency in the observation data and can be applied by operators and port managers to improve the reliability of ship navigation in shallow waters and coastal areas.

6 A Dynamic Human Reliability Model for Marine and Offshore Operations in Harsh Environment

Abstract

Human activities are a predominant part of the daily tasks in offshore operations from design, construction, operation, management and maintenance. It is not surprising to observe a major means of failures related to human error, since humans are susceptible to making mistakes. Due to the high level of uncertainty in human activities, predicting all causes of human error is not an easy process. This may lead to inaccurate results, which may affect the overall safety and reliability of marine operations. The reason is that evaluating human endurance during activity on board is a key factor in minimizing the risk of human failure. This study aims to study uncertainties over the time of a marine operation to estimate accurate human reliability assessment. A framework is developed to model the uncertainty of human performance factors by considering a hydrodynamic analysis of the structure along with a subjective analysis of human activities under different weather conditions. Subsequently, a model based on Dynamic Bayesian approach is developed to evaluate the effect of time duration on human performance during the operation. The developed methodology has been applied to a case study of an offshore vessel storing extracted oil. The framework demonstrates that probability of human failure increases towards the end of its operational days; however, the intensity in the variation of human reliability is highly dependent on weather condition. The present study is able to improve the safety of human life in marine operations by predicting the reliability of performances as a function of time during a specific operation.

Key words: Human error, harsh environment**,** Dynamic Bayesian Network, failure rate

6.1 Introduction

Human error is one of the main failure causes in everyday functioning. It is connected to human behaviour that is considered undesirable and somehow unpredictable due to high uncertainty involved in human performance. When changes occur in the environment and working area of any operation from standard condition to non-standard condition such as harsh environment, then human error plays an imperative part in operational failure. Controlling the health of the operation is a challenging task and subject to various uncertainties and sources of failure in technical, organizational and human activities. Amongst these general classifications, human performance has a high failure rate (Islam et. al, 2017a) and involves much uncertainty due to lack of supporting empirical evidence. Hence, developing a precise framework to model the uncertainty of human performance is essential to mitigate risk of human failure during marine operations in a harsh environment. Risk assessment should be considered in designing, construction, maintenance and operation to enhance the safety and reliability of marine and offshore structures (Noroozi et al. 2014). However, risk assessment is associated with various uncertainties that have a severe economic impact on projects due to potential failures. Lack of adequate information about previous failures and useful data for developing a probability model are the main impediment in the assessment and quantifying of operational risks. Moreover, selection of an appropriate quantitated risk methodology that best represents human error uncertainty in a complex situation is challenging. Khan et al. (2015) identified three main sources of information required for component failures estimation. These are: (1) expert judgment, (2) experience and knowledge data accumulated from local field and (3) data and information shared across industries operating in a harsh environment. However, human beings cannot be regarded as a component to estimate the failure by just using data mining or experience, due to the high level of uncertainty associated with human performance. In system reliability, the component is referred to as structural or technical systems such as, crane, electrical chip boards and dynamic positioning (DP) system etc. All these components are necessarily involved with human activities and their imperative rule should not be neglected to prevent the unexpected failures due to human error. Therefore, it is essential to quantify human error by considering human performance shaping factor (PSF) using either expert judgment or real simulation. This causes a great deal of uncertainty for computing human error probability (HEP). There is no guarantee that the expert team will consider all aspects of human error, especially in a harsh environment where there is a lack of sufficient experience. This means that there may still be a chance of existing unpredicted source of human error, despite precise monitoring to detect all potential failures on a system being carried out.

HEP assessment techniques are initially based on research in the nuclear industry and most of them are developed based on expert judgment techniques. These techniques include; Successive Likelihood Index Method (SLIM), Technique for Human Error Rate Prediction (THERP), Justified Human Error Data Information (JHEDI), and Human Error Assessment and Reduction Technique (HEART) (Kirwan et al. 1997; Kirwan 1997, 1998). There has been a great deal of research to assess HEPs using the aforementioned methods by many researchers (Abbassi et al. 2015; DiMattia 2005; Miller and Swain 1986; Noroozi et al. 2013; Noroozi et al. 2014; Raafat and Abdouni 1987; Zamanali et al. 1992).

However, at a glance, it is clear that the main focus of previous studies was to evaluate a stationary process of human error regardless of duration of human activities. Although the assumption of neglecting the variation in human activity over a longer period could be generally true under normal conditions, it can lead to underestimated results as site environments change quickly in a harsh environment. Therefore, it is essential to understand what the trend of human reliability is in the case of time-dependent parameters included in probability estimation, and, how human performance will be affected by harsh environment.

In recent years, Bayesian Network methodology has been developed in the field of Artificial Intelligence (Nielsen and Jensen 2009). It is common agreement that this causal network based method is a powerful tool to calculate the probability of events given the observation/evidence of other events in the same network based on graph theory (Ghosh 2008). Recently, Dynamic Bayesian Networks (DBNs) have been widely used in engineering decision strategy (Arzaghi et al. 2017; Bhandari et al. 2016; Friis-Hansen 2000; Khakzad et al. 2011, 2013). DBN offers a flexible probabilistic network to model time dependencies of a set of random variables in time domain (Hosseini and Takahashi 2007) (Friis-Hansen, 2000). In the present study, a model using BN is developed to assess the influencing parameters that cause human failure as a function of time under different environmental conditions. For this purpose, to model the effect of extreme response and human feedback during an operation in a harsh environment a real simulation of the floating structure is considered. Further, to model the effect of time on human performance, a human reliability framework is developed based on the Dynamic Bayesian approach to estimate the effect of human fatigue on HEP during the specific time of marine operations under three different weather conditions. The outcome of this research is practical for industries to understand the reliability of human performance as a function of time and the ability to improve the safety of human life in marine operations.

6.2 Methodology Development

The imperative role of human error on the performance of a system has been considered in previous studies. This study develops a novel methodology to evaluate human performance on the floating structure for a distinct period of marine and offshore operation subjected to the harsh environment. The present framework proposes a DBN to consider different aspect of influencing factors that cause human failure. A schematic illustration of the proposed methodology is illustrated in Figure 6.1.

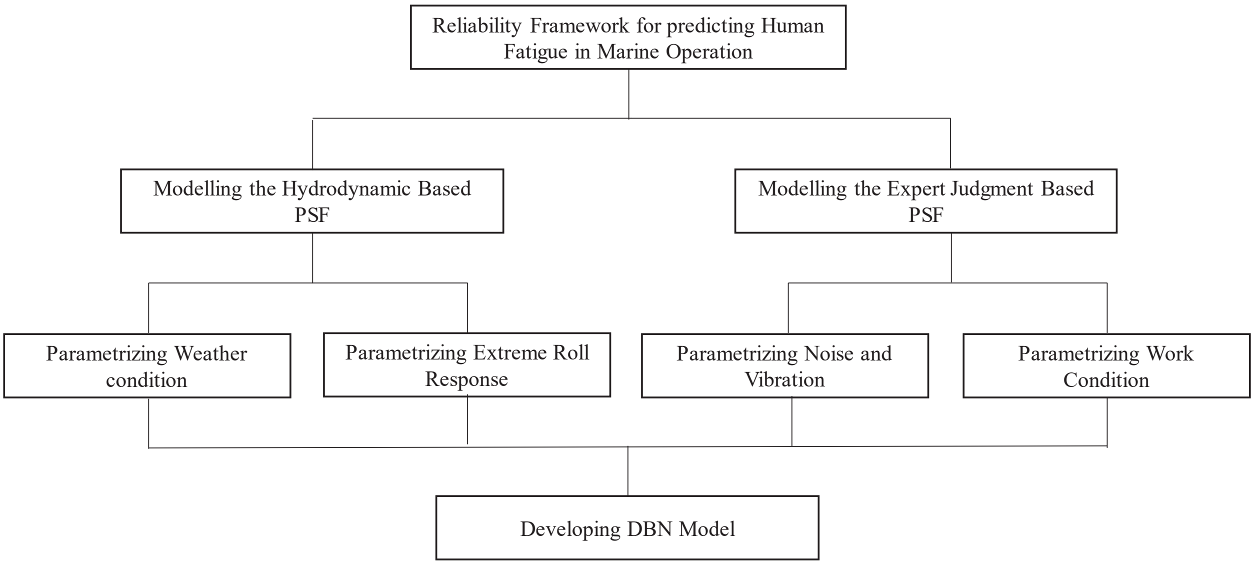


Figure 6.1 Developed framework for evaluating human fatigue during a marine operation

6.3 Determining Human Reliability Function

Human performance can improve due to increase in knowledge and experience. However, in a long period of a specific operational time, human error will increase due to critical level of fatigue. In this case, dynamic analysis of human performance is necessary to understand time variation of human reliability during the operational time. At the early stage of the project with respect to the entire time of the operation, labour is not expected to be a considerable error, however performance will be affected notably towards the final stage of the working period due to high level of fatigue or change in environmental conditions. In order to include the effect of time on human error, an exponential distribution (Nielsen and Jensen (2009) is applied to estimate the human reliability:

$$R(t) = \left[1 - \exp\left(-\lambda(t - t_0)\right)\right].H(t) \tag{6.1}$$

$$H(t) = \begin{cases} 1 & t \geq t_0 \\ 0 & t < t_0 \end{cases} \tag{6.2}$$

where, λ is a constant failure rate for the exponential distribution, H(t) is Heaviside step function to consider the fact that human reliability has meaning only for the operation that, and is the time that the operation will start.

6.4 DBN implementation to updated HEP

A Dynamic Bayesian approach is considered to model human reliability over time in different weather conditions. A brief overview on Bayesian Networks (BNs) is discussed in Pear and Russel (2000), while a more comprehensive theoretical background on BN is found in Pear (1988) and Nielsen and Jensen (2009). Moreover, many software packages are available for the computation of BNs, as discussed in Murphy (2001). In the following paragraph, a brief introduction on DBN is provided as a tool to study the effect of time on human failures over a specified period.

DBN is an extension of ordinary BN that is used for evaluating a set of random variables over a discretized time line. DBN can be interpreted as a generalization of Markove process models, which commonly been applied for the modeling of deterioration as described in D. Straub (2009). Markov deterioration processes are explained as conditional dependency and independency over time for a given condition at time t_1. Therefore, the condition at any further time $t_{i+1} > t_i$ is statistically independent of the condition of any previous time step, $t_{i+1} < t_i$. Accordingly, each sequence of time slice consists of one or more BN nodes. The slices are connected by directed link from nodes in slice i to nodes in slice $i+1$. Correspondingly, a node at time slice i+1 can be conditionally dependent on its parents at the previous time slices i and the present time i+1 simultaneously. The conditional probability table for a set of stochastic variable X at each time step is then expressed as, $P(X^{(i+1)} \mid X^i, Pa(X^{(i+1)}), Pa(X^i))$. Finally, the joint distribution of a set of X random variables in i+1 time step will be achieved as a consequence of Bayes Rule, (Nielsen and Jensen (2009) as explained in Equation (6.3):

$$P\left(X^{i+1}\right) = \prod_{j=1}^{m} P\left(X_j^{i+1} \mid X_j^i, Pa\left(X_j^{i+1}\right), Pa\left(X_j^i\right)\right) \quad i = 1,\ldots,n \quad ; \quad j = 1,\ldots,m \tag{6.3}$$

where, i is the time step that joint distribution is supposed to be computed from previous time slice, while j is the number of BN nodes associate with next time slice to consider conditional dependencies and independencies. States of any system described as a DBN satisfy the Markovian condition that assumes the state of a system at time t_i depends only on its immediate past at t_{i-1}, (D. Straub, 2009).

In this study, a fatigue model based on the DBN is developed to predict human behavior in marine operations due to the long term on board activities. For this purpose, that the factors that have imperative effects on causing human fatigue are considered in this study as suggested by (Islam et al. 2017a; Islam et al. 2017b) and represented as human Performance Shaping Factors (PSFs). As suggested by Islam et al. (2017a), the most important shaping factors that can cause human fatigue are;

1. Weather Condition (F1), defined as the long term occurrence of extreme wave heights (Hs) and zero up crossing wave period (Ts) in a harsh environment,
2. Ship Motion (F2), defined as the critical response of the vessel encountering extreme wave heights,
3. Noise and Vibration (F3) and
4. Work Environment (F4) defined as the condition that makes the situation intolerable for the personnel on board.

Each of these PSFs should be assigned probability of occurrence to represent the uncertainties that involve these factors. These probabilities can be derived either from simulation, or expert judgment depending on the type of the PSF and the availability of the historic data (Abaei et al. 2017; Islam et al. 2017b). In this study, the probability table for the root nodes of F1 and F2, i.e. hydrodynamic related PSFs are obtained based on the proposed hydrodynamic framework developed by Abaei et al. 2018a, Abaei et al. (2017) and Chen et al. (2004) for an offshore operation in a harsh environment. The logical probabilities for other factors F3 and F4 are derived based on the Expert Judgment represented by Islam et al. (2017a) for similar marine operations in Harsh Environment. An illustrative DBN of the proposed methodology to estimate the human fatigue reliability over time in the marine operation is represented in Figure 6.2.

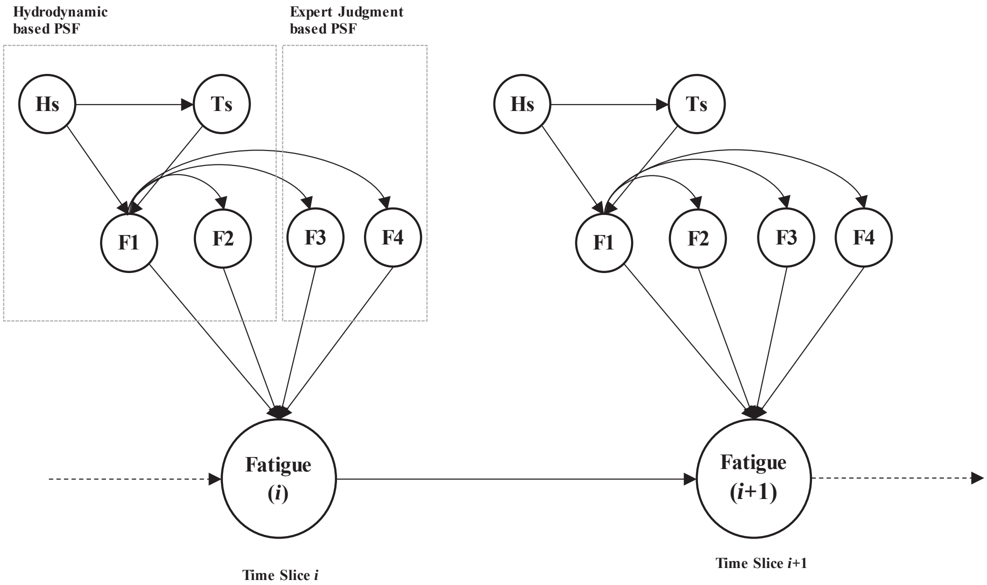


Figure 6.2 DBN for modelling time varying human fatigue in marine operation

6.5 Construction of Conditional Probability Tables (CPTs)

To implement the DBN model for human fatigue inference, the network needs to be parametrized with logical numbers that represent the probability for the root nodes and the conditional probabilities for the link. The probabilities for the root nodes are estimated based on hydrodynamic analysis and using expert judgment process as mentioned in section 2.2. However computing the conditional probability tables for the fatigue nodes is not an easy process as it is a subjective estimation and there is no relationship available for these nodes. Although, it is common to obtain such probabilities from statistical analysis of a large amount of training data, it is not recommended by (Co et al. 1999; Ji et al. 2006) for human reliability assessment. However, based on recent studies on large scale subjective surveys (Ji et al. 2006; Rosekind et al. 2000; Sherry 2000) for parametrizing the BN model, a “Noisy-Or” principle does provide a favourable solution.

The Noisy-Or model has three assumptions, the first one is its casual inhibition. It is based on three assumptions, first, a cause-effect relation between the parameters, second exception independence, means that each causes are mutually exclusive, and third it is accountability which is assumed an event can happen if and only if at least one cause is occurred, (Neapolitan 2004). These assumptions help to introduce conditional probability tables for the model. In the noisy-or principle, all states of the nodeF1, F2, …, Fn can be defined in a binary format. These states represent all possible conditions of a variable, e.g. "Fatigue = Yes" or "Fatigue = No". Therefore, any event such as Fi = Yes, will cause human fatigue unless an inhibitor or a preventing factor prevents the error in human performance. Finally, the probability qi defined as, (Ji et al. 2006):

$$\prod_{1\le j\le n} q_i = P(Fatigue = no \mid F_1, F_2, ...F_i, ..., F_n) \tag{6.4}$$

Therefore, the Noisy-Or model assumes that the presence of each shaping factor, such as extreme roll response of the vessel, F2 = "Extreme Roll Angle", is sufficient to produce the presence of the human fatigue and its effect is independent of the presence of other causes. The same subjectivity representation is recommended by Islam et. al, (2017a) and Ji et al. (2006) . In other words, the presence of fatigue will trigger human malfunction if one of the influence factors occurs. This assumption is reasonable in reality though it is a subjective points of view as investigated by (Chen and Moan 2004). In addition, previous studies demonstrated this point from the conducted experiments and expert judgments that each of these PSFs can independently cause human error (Chen et al. 2004, Ji et al. 2006). A graphical representation of the Noisy-Or principle is illustrated in Figure 6.3.

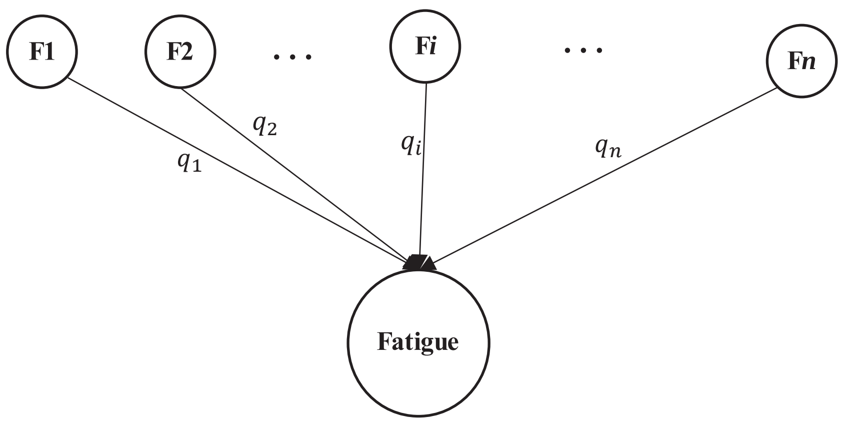


Figure 6.3 A schematic preview of the Noisy-Or Principle.

Due to lack of available data for human activities in marine operations, the process for construction of CPT is always a crucial step. This is a particularly thorough process especially for the factors that have no physic basis, such as F3 and F4. As a result, it is necessary to rely on the survey data gathered from expert judgment by conducting a questionnaire survey among experienced seafarers around the world as presented by Islam et al. (2017a). In this approach, there are three steps to construct the CPT table. First a questionnaire should be developed to determine the impact of desired child nodes (variables); second, a survey method such as Monkey link should be created to conduct the data collection; and third, the collected data needs to be translated to a probability to represent the CPT for the desired links in the probability network. In this study, CPT table is constructed based on the conducted survey by Islam et al. (2017a). The other factors relating to the hydrodynamic performance of the vessel will be obtained based on the stochastic analysis of the structure and a designed wave profile. The results are then extracted and changed to a probability model with the fact that a proper limit is identified to understand the tolerable level for human performance on the vessel.

6.6 Application of the Methodology: Case study

6.6.1 Scenario development

To illustrate different steps of the methodology, a practical case study is considered for evaluation of human reliability during marine operation on Sevan 1000 Floating Storage Unit (FSU) encountering a harsh environment. This structure is designed to operate in the Mariner field in the North Sea (Hanssen 2013). The structure is a storage unit incorporating a main hull with overall length of 85 m and draft of 30 m. A part of the case study investigates human performance based on the extreme response of the vessel when subjected to different incident waves to model the Hydrodynamic Based PSF nodes (See Figure 6.3). For this purpose the criteria and the operational limits similar to Chen et al. (2004) and Hanssen, (2013) will be applied to translate the effect of structural response to reasonable human reliability. Therefore, the structure will be simulated in an actual harsh environment subjected to a stochastic wave train. A safe level will then be considered for human activity on board to evaluate a true condition of human failure during the operation. The other factors will be modeled based on expert judgment and the available precursor data for the marine operation.

6.7 Results and discussions

With increase in the duration of human activity in the operation, the uncertainty of human performance increases notably, which is necessary to consider for time-varying effect of human error in reliability assessment. Based on Maritime Labor Convention (MLC), the number of working hours on ships should be eight hours a day (Lillie 2008), under normal circumstances, with one day of rest and a maximum of 14 hours in any 24 hour period. In general, MLC recommends a short term strategy that working hours on ships should not exceed 49 hours per week. However these rules are still not considered as having reliable strategies for evaluating the long term prediction of human performance during an extended operational time. As suggested by Ji et al. (2006) it is necessary to estimate human endurance to understand how individuals will gradually be exhausted by increasing the time. To return labor to normal conditions, a long term reliability estimation should be performed to analysis the maximum endurance of human performance. This will assist individuals to be granted a proper rest period to prevent build-up of human fatigue. Therefore, in this study, the period of 100 days is considered to evaluate performance of human ability staying on board. In the proposed DBN, 5 different time slices are considered for modeling human fatigue. In order to obtain the hydrodynamic based factors, OrcaFlex software is employed to model the sea environment and evaluate the stochastic response of the vessel under the different sea conditions. For this purpose, eleven sea states are considered, these waves are based on the approach proposed by Abaei et al. 2017. To identify the severity of the wave condition, the profile is divided into three level of intensity, Normal, Moderate and Extreme. A summary of the significant wave heights and the zero up crossing wave period are explained in Table 6.1.

Table 6.1 The discretized Sea states used to model sea environment

Weather Condition	Sea State	Significant Wave Height, Hs (m)	Peak Spectrum Wave Period, Ts (s)
Normal 70% of minimum Percentile	1	Hs <0.65	2.58
	2	2.15	4.69
	3	3.65	6.12
	4	5.15	7.62
Moderate 70% to 90% of highest Percentile	5	6.65	8.26
	6	8.15	9.14
	7	9.65	9.94
Extreme 10% of highest Percentile	8	11.15	10.69
	9	12.65	11.39
	10	14.15	12.04
	11	Hs >15.65	12.60

Subsequently, these eleven sea states are transferred to a spectral analysis to obtain the wave profile of the sea environment. An illustrative of the developed wave profile is shown in Figure 6.4. The profile is divided into three section for identifying the intensity of the sea condition based on the human tolerable operational limit (Hanssen, 2013) as 5 meters is considered for normal operation (Chen et al, 2004).

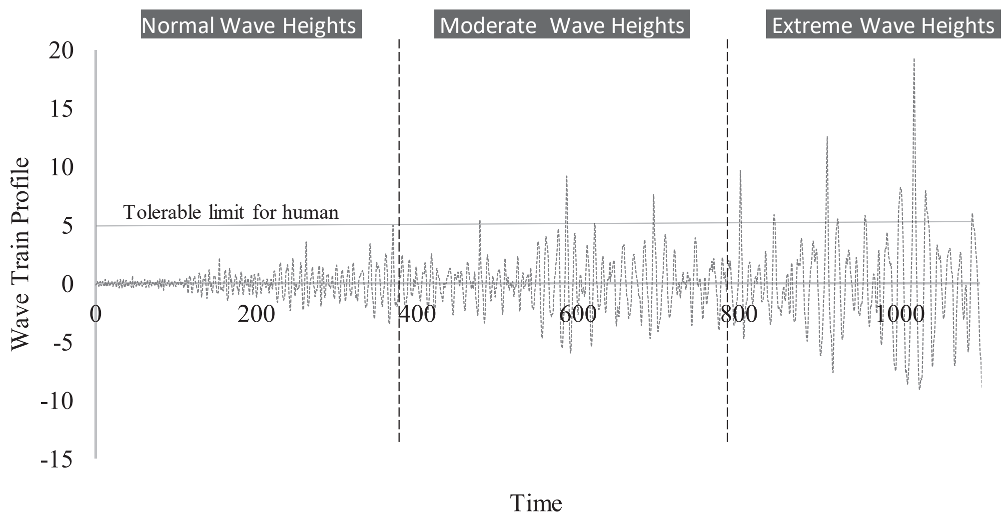


Figure 6.4 Developing wave profile to model sea environment for evaluation response of the vessel

Considering the designed wave profiles, the probability density function for the occurrence of the wave height is estimated using Maximum Likelihood Estimation Method (MLE) as recommended by Abaei et al. (2017) and the result represented in Figure 6.5. To identify three levels in the wave profile, a 70% percentile of the minimum observed wave heights are considered as Normal Condition, 70% to 90 % bound of the minimum wave heights defined as Moderate and 10% percentile of the highest encountering waves considered as the Extreme conditions.

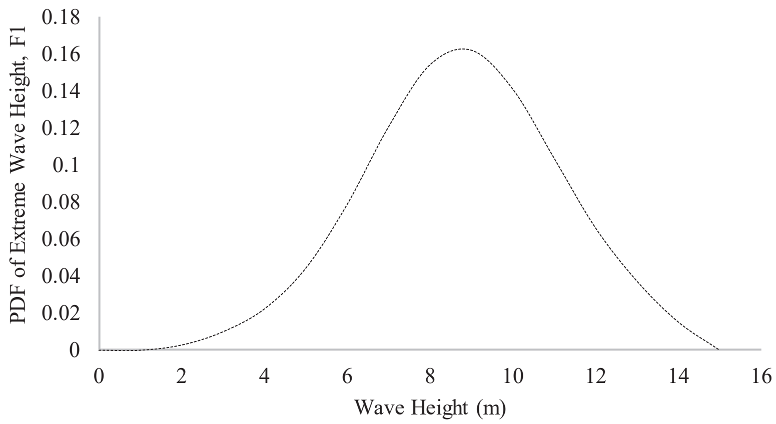


Figure 6.5 PDF of extreme wave heights derived from stochastic wave profile presented in Figure 6.4.

The designed wave train in Figure 6.4 is modeled in OrcaFlex and the hydrodynamic performance of the vessel is estimated by the extreme response of the roll degree. The result of the stochastic response analyzed and the PDF of the response obtained using MLE method is plotted in Figure 6.6. The same approach is applied for dividing the response to the three levels of Normal, Moderate and Extreme weather conditions.

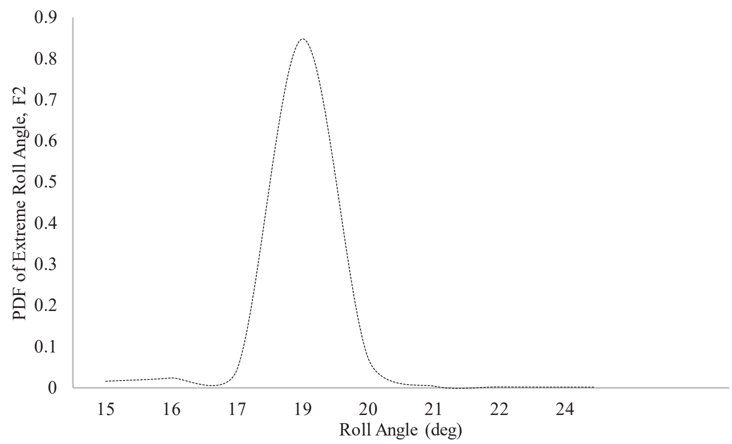


Figure 6.6 PDF of extreme roll angle due to subjecting stochastic wave profile presented in Figure 6.3.

Based on the conducted survey of 236 experts in the field of marine operations on the floating structures presented by Rabiul et al. (2017a), the probability of the influencing parameters on human fatigue on different levels of weather conditions for Noise and Vibration, and Work condition obtained is represented in Figure 6.7.

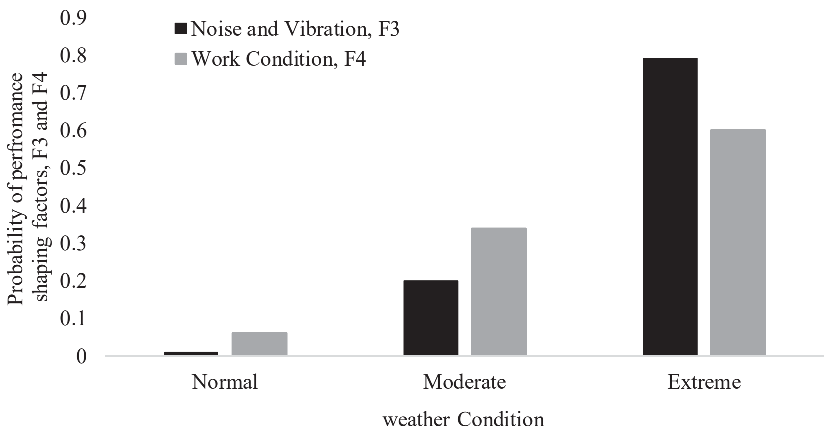


Figure 6.7 Probability of influencing human factors, Noise and Vibration (F3), Work Condition (F4) in different weather severity

To achieve the time domain human reliability assessment, the probability obtained for quantifying the PSFs and the values entered in the DBN model are presented in Figure 6.2. The probability value for the fatigue node in each time step is estimated based on the approach described in section 2.2 of the presented methodology. In this study, GeNIe software is employed to perform the reliability analysis of human fatigue over the introduced time slices. The analysis conducted for all three weather conditions and the reliability of human fatigue during the 100 days of the operation is presented in Figure 6.8. The results demonstrate the effect of operational time on decreasing reliability of human performance in a marine operation. The important point is that, for the considered case study, reliability of human performance will not touch zero under normal and moderate conditions, however it will decrease over 100 days for the extreme weather condition. By assuming that the acceptable safe level for probability of human fatigue is 1E-5, Chen et al. (2004), the proposed framework for the conducted case study confirms that a person can continue continuous duty up to 60 days under normal conditions, 40 days under moderate conditions and 20 days under extreme conditions. The operation is otherwise prone to being subject to human failures increasing day by day. The presented results of this study are imperative for improving the safety of human operation in different sea environments. The developed framework is capable of assisting authorized company to consider a reliable decision for scheduling the best time of the operation and identifying a substitution timetable to minimize the risk of human failure.

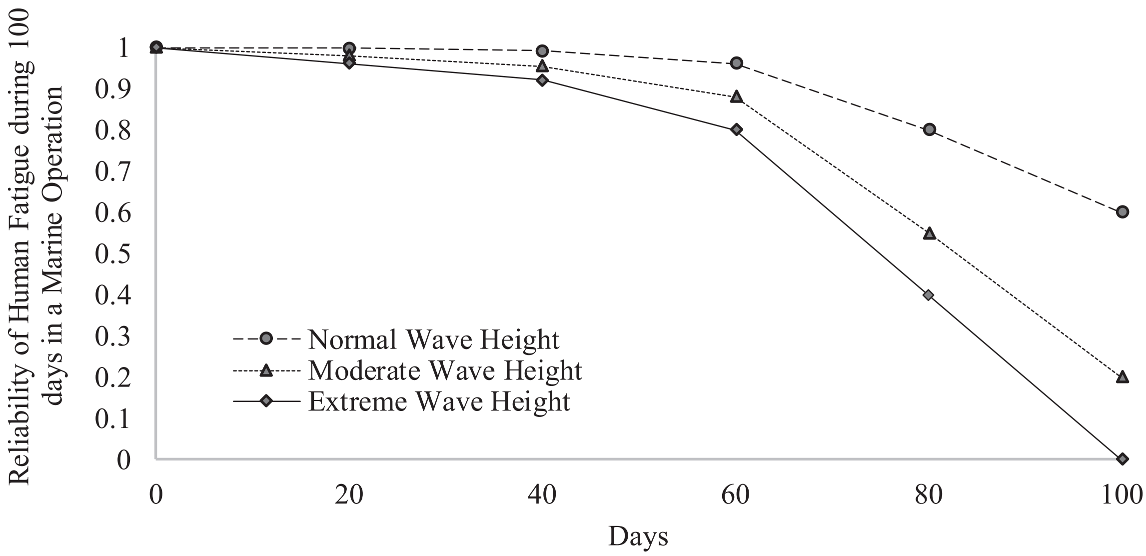


Figure 6.8 evaluating reliability of human fatigue in a marine operation for different wave conditions

6.8 Conclusion

In this study, a framework is developed to evaluate human fatigue during a marine operation. A DBN based model is presented for the uncertainty in human performance and estimating human reliability in a defined period of marine operation. A hydrodynamic analysis and a survey based approach is applied to a model influencing factors on human performance. The proposed framework can provide more realistic results on reliability of human performances during a period of marine operation. For the demonstrated case study, the reliable time for a person working on board is two months under normal conditions, however it is less than three weeks in an extreme environment. The present methodology has the ability to be considered as a basis for future decision making assessment to improve the safety of human life in marine operation while conducting duties in different weather conditions.

7 Conclusions and Recommendations

The proposed research attempts to undertake risk and reliability assessment of marine operations by identifying possible accident scenarios and presenting an advanced technique for predicting possible failure events. In this thesis various frameworks are developed to evaluate safety of marine operations subjected to random sea conditions. For the first objective, a new methodology based on BN is developed to integrate reliability assessment and hydrodynamic analysis of a marine structure for optimizing the safety of the structure operating in different sea conditions. The developed methodology is applied to a tensioned floating cylinder as a case study and the optimum design parameters of the mooring line are identified. It is found that the structure can tolerate an extreme wave height with optimum critical surge response of $X_C = 3.5$ m. To address the second objective, a novel approach is developed as an efficient tool to evaluate the hydrodynamic performance of the marine structure under storm conditions. The approach proposed a method for constructing a storm by superimposition through intensifying a wave train function in different sea states. This approach is capable of efficiently evaluating hydrodynamic response of the structure encountering a storm in a single time frame with the result of reduced computation cost of simulations. The advantages of the proposed framework were demonstrated by simulating an FSU in a storm condition and the results showed that the structure would exceed the survival condition if the storm passes the significant wave height level of 12.65 meters. Furthermore, the results of this study demonstrated that the proposed approach can be used as a useful framework for future risk and reliability analysis considering the dynamic behavior of a floating structure to generate essential data for risk and reliability assessment of marine structures.

The third objective is achieved by developing a methodology to assist in making the optimum decision to improve safety of the marine structures under evolving operational conditions. The application of the framework was investigated through simulating an FSU in a storm condition with different angles of attack. The results of the analysis indicated that in a flooded FSU, evacuation is the optimum decision alternative if the wave heights exceed H_s=8.15m for the incident wave angles of 45^0 and 180^0, and H_s=14.15m, for 270^o. This methodology can be used as an effective tool for quick and robust decisions framework, while incorporating the uncertainty associated with the hydrodynamic performance of a floating structure in a harsh environment. The fourth objective is attained by developing an advanced reliability framework for predicting the grounding failure of ships transiting in shallow waters. The hydrodynamic responses of a vessel are evaluated for different ship speeds and incident wave heights, then the estimated DUKC results are adopted to develop the HBM. As a case study, the performance of the vessel was assessed when it entered the coastal zones in North-East Queensland with a water depth of 12 m. The results of the study demonstrate the need for an NHPP model in ship grounding assessment. The proposed framework can predict the grounding likelihood of a vessel more accurately by considering the time dependency in the observation data and can be applied by operators, port managers and e-navigational tools to improve the reliability of ship navigation in shallow waters.

The final objective is achieved by assessing human fatigue during a marine operation. A DBN model is presented for estimating human reliability while considering the uncertainties associated in human performance during a period of marine operation. In order to investigate the influencing factors on human activities, a hydrodynamic analysis and a survey based approach is applied to the proposed model. As a case study, the reliable time for an individual working on board is investigated and the results demonstrate that two months is a safe period in normal conditions, however it is less than three weeks in an extreme environment. The present methodology has the ability to assess the reliability of human performance to improve the safety of their life in marine operations.

7.1 Recommendations

The present work attempts to introduce new methodologies to assess the risk and reliability during the operations of marine systems. This study can be further extended as follows:

(i) Integrating different types of simultaneous failures to evaluate the reliability of marine operations in more robust conditions;

(ii) Considering advanced optimization models such as a training network for improving the decision making framework during design phase of marine structures;

(iii) Developing methodologies to apply proper countermeasures in marine systems that are able to protect critical infrastructure from uncommon events such as terrorism attacks;

(iv) Improving availability of the marine and offshore structures by prioritising with higher risk to the operation;

(v) Reliability modelling of the infrastructure systems found within large marine floating structures or offshore wind farms with the aim of using mixed-resolution data for optimizing maintenance planning of the system;

(vi) Developing a realistic data management approach for marine failure root cause analysis and conducting a study toward automated and integrated data collection-standardising workflow processes for the offshore wind industry;

(vii) Developing an advanced statistical method to analyse condition monitoring data collected from experimental or dynamic modelling of marine structures.

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